IE UNIVERSIDAD

TESIS DOCTORAL / DOCTORAL DISSERTATION

Análisis exhaustivo de los Fondos de Inversión: Una investigación Empírica: El Caso Colombiano / A Comprehensive Analysis of Investment Funds: An Empirical Investigation – The Colombian Case

Iván Andrés Montoya Moreno

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ABSTRACT

This study uses the most comprehensive dataset ever prepared to study investment fund performance in Colombia in terms of both number of funds and number of attributes. In the Colombian market, we empirically study i) the performance of investment funds and the style classification, ii) the link between management fees and performance among investment funds, and iii) the factors that may explain the differences in performance across these funds. We seek to understand whether i) investors have the right information to evaluate fund performance and ii) investment advisor compensation is determined according to the level of performance or some other set of determinants. We provide useful benchmarks for evaluating relative past performance, and the methodology employed is a useful descriptor of fund styles and performance. We find that investment funds adopt styles that do not deviate markedly from passive benchmarks and that few take significant positions away from the index. We provide evidence that the local classification provided either by the company advisory or even by the regulator has relatively little power in explaining differential fund performance. No evidence exists that argues that advisory companies in Colombia intentionally present higher alphas that result in more value added. However, we realize that all of the information that provides a consistent view of investment decisions in Colombia needs to be systematically collected by the regulator. We provide new evidence on products offered by company advisors in this market. In particular, our results on the distribution of fund styles suggest that overall investment funds tilt toward money market investing, which might be a reason that, historically and on average, funds cannot beat the market after costs. From the standpoint of an

investor, drifts in style with poor past performance introduce variability that deserves monitoring. Our empirical evidence extends the current finance literature for non-U.S. funds because we find a positive relationship between fees and performance. Relatively sophisticated investors in Colombia appear to penalize funds for poor performance. The elasticity of demand or performance sensitivity for investment funds in Colombia seems to influence the determinant of fees. In our investigation, we encountered common determinants of investment funds' performance according to previous research but also found some important differences. This analysis will also help governments and regulators formulate their policies because the effect of incentives on risk-adjusted performance should have important policy implications.

ABSTRACT (Spanish Version)

El presente estudio usa el conjunto de datos más exhaustivo jamás preparado localmente para estudiar el rendimiento de los fondos de inversión en Colombia, tanto en número de fondos como en número de atributos. Estudiamos empíricamente en el mercado colombiano i) el rendimiento de los fondos de inversión y la clasificación de estilos; ii) la relación entre las comisiones de gestión y el rendimiento de los fondos de inversión, y iii) los factores que pueden explicar las diferencias de rendimiento entre estos distintos fondos. Este trabajo busca entender si i) los inversionistas cuentan con la información adecuada para evaluar el rendimiento de los fondos y ii) si la compensación de los administradores de los fondos de inversión está determinada según el nivel de rendimiento del fondo o si existen otros factores asociados. Ofrecemos índices de referencia ("*benchmarks*") útiles para evaluar relativamente el rendimiento histórico y la metodología empleada ha sido un descriptor útil para analizar los estilos y el rendimiento de los fondos. Encontramos que los fondos de inversión adoptan estilos que no se desvían sustancialmente de los índices de referencia pasivos y que algunos pocos toman posiciones alejadas del índice. Ofrecemos evidencia que la clasificación local proporcionada por la compañía administradora del fondo e incluso la suministrada públicamente por el regulador tiene relativamente poca capacidad de explicar el rendimiento de los fondos de manera diferenciada. No encontramos evidencia que pruebe que las compañías administradoras de fondos de inversión en Colombia estén presentando intencionalmente alfas más elevadas que resulten en un mejor valor agregado. Sin embargo, observamos que toda la información de los fondos que proporciona una visión consistente

para las decisiones de inversión en Colombia necesita ser recopilada sistemáticamente de manera más adecuada por parte del regulador. Ofrecemos nueva evidencia sobre los productos ofrecidos por las compañías administradoras de los fondos de inversión en este mercado. Concretamente, nuestros resultados en la distribución de estilos de fondos indica que, por regla general, los fondos de inversión en Colombia suelen inclinarse hacia la inversión en "*money markets*" o de corto plazo, lo que contribuiría a explicar por qué, tradicionalmente y de media, los fondos son incapaces de superar el mercado después de descontar costos. Desde el punto de vista de un inversionista, los cambios de estilo con rendimiento histórico pobre introducen una variabilidad digna de ser monitoreada. Nuestras pruebas empíricas amplían la literatura financiera actual para los fondos de inversión diferentes a EE. UU., ya que detectamos una relación positiva entre las comisiones y el rendimiento. En Colombia, inversionistas relativamente sofisticados parecen penalizar los fondos con un bajo rendimiento. La elasticidad de la demanda y la sensibilidad al rendimiento de los fondos de inversión en Colombia parece influir en la determinación de las comisiones. En nuestra investigación encontramos algunos determinantes comunes del rendimiento de los fondos de inversión en relación con investigaciones previas, pero también detectamos importantes diferencias. Este análisis también ayudará a los gobiernos y reguladores a formular sus políticas debido a que el efecto de los incentivos en el rendimiento ajustado al riesgo debería tener implicaciones importantes en la reglamentación.

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1. INTRODUCTION

The distribution of wealth among investors, investment companies, and portfolio managers in the investment fund industry has been of significant interest to researchers and practitioners given the agency issues that arise when investors delegate portfolio management decisions to third parties (i.e., investment companies and portfolio managers). In addition, investors are increasingly interested in investment fund selection, demanding detailed investment fund information and advice.

Investment advisors and portfolio managers play a pivotal role in portfolio management activities because they conduct research and make fund investment decisions on behalf of investors (Baumol et al., 1990). Investors also have an obvious interest in evaluating their portfolios' performance (Dahlquist et al., 2000). Arguably, delegated portfolio management is one of the most important agency relationships that intervenes in the economy, with a possible impact on financial market and economic development at a macro level (Stracca, 2006).

The growth of the mutual fund industry started in the United States, as stated by Ferreira et al. (2012). Given that the mutual fund industry plays an important role in the development of financial markets, the growth in investment funds has spread broadly to other countries, including emerging markets (Khorana, Servaes, and Tufano, 2005). For instance, Ferreira et al. (2012) point out that the assets under management outside the United States grew from 38% in 1997 to 54% of total assets in 2007. Such growth is not the exception in the Colombian context. The public interest in the Colombian investment fund industry has grown rapidly. At the end of 2015, the investment fund industry in Colombia managed financial assets exceeding COP 56 billion (approximately USD 17.5 billion[1]), whereas this figure was COP 29.3 billion[2] in 1999 (approximately USD 9.2 billion), reflecting growth of 92% from 1999 to 2015 and approximately 6% of the Colombian GDP. Additionally, the number of investment funds has grown dramatically, from 198 funds in 2009 to 403 funds at the end of 2015. During 2015, more than 71% of the investment fund industry in Colombia is managed and controlled by trust companies ("*fiduciarias*"), and the rest is managed by stock brokers ("*comisionistas*"). Trust companies have remained the most representative type of advisory company in the Colombian context and still manage financial assets exceeding COP 40 billion (approximately USD 12.53 billion[3]).

Colombian investment funds are surveilled by the Superintendence of Finance in Colombia (Colombia's SEC). On a monthly basis, Colombia's SEC only publicly reports daily fund returns, total assets under management, number of investors, net flows, and a basic style classification. Any information that investors want to obtain and assess relative to their investments, in addition to the information publicly available from Colombia's SEC, needs to be obtained from the technical reports issued by the advisory companies.

Although the investment fund industry in Colombia has had a strong impulse in terms of development and expansion and is partly favored by current national regulations that, in part, have been inspired by the United States and some European countries, ample room to improve still exists before converging

[1] Converted into USD at the COP exchange rate on December 31, 2015 (USD 1 equal COP 3,191.68).
[2] Information extracted and analyzed from the Superintendence of Finance in Colombia.
[3] Converted into USD at the COP exchange rate on December 31, 2015 (USD 1 equal COP 3,191.68).

to the standards of more developed markets. The experience and the market itself showed the improvements needed to enact stronger requirements for the disclosure of clear and sufficient information directed to investors, given that the public information reported by Colombia's SEC and the information reported by advisory companies in prospectuses and technical reports are not easily collected by investors on a timely basis to evaluate the performance of their investments. The current style classification, which is not objectively determined, does not allow for differences in future returns to be explained. No available benchmarks exist, and the regulator does not publicly report information on investment funds' fees or specific regulations on portfolio holdings or manager compensation.

Many authors attempted to explain the performance of investment funds by employing passive benchmarks and several fund characteristics as potential determinants of future fund performance, such as fund size, age, fees and expenses, loads, turnover, flows, and returns.[4]

An important debate in the literature is i) whether the design of mutual fund management fees are related to performance (e.g., Jensen and Meckling, 1976; Grinblatt and Timan, 1989; Zajac and Westphal, 1994; Guay, 1999; Deli, 2002; Ross, 2004; Massa et al., 2009), ii) whether such design provides managers with the right incentives to align their interests (e.g., Battacharya and Pfleiderer, 1985; Starks, 1987; Stoughton, 1993; Admati and Pfleiderer, 1997; Christoffersen and

[4] See, for example, Jensen (1968); Grinblatt and Titman (1989a), Ippolito (1989); Carhart (1997); Sirri and Tufano (1998); Coles, Suay, and Woodbury, (2000); Deli (2002); Elton, Gruber, and Blake (2003); Golec and Starks (2004); Chen et al. (2004); Farnsworth and Taylor (2006); Massa and Patgiri (2009); Gil-Bazo and Ruiz-Verdu (2009); Warner and Wu (2011); (Ferreira et al., 2012).

Musto, 2002; Gómez and Sharma, 2006; Gil-Bazo and Verdú, 2009; Dybvig, Farnsworth and Carpenter, 2010; Agarwal, Gómez, and Priestley, 2012), and iii) whether the management styles are objectively and empirically determined for performance measurement and compensation (e.g., Sharpe, 1992; Brown and Goetzmann, 1997; Li and Tiwari, 2009; Garleanu, Panageas and Yu, 2017).

In the investment fund industry, style classification and investment objectives are widely used to characterize differences between investment funds (e.g., Sharpe, 1992; Brown and Goetzmann, 1997; Chen et al., 2002). For agency reasons, understanding a fund's styles classification is important, given that the behavior of investment fund managers might be inclined to some consideration beyond diversification or portfolio return maximization (Chan et al., 2002).

Previous research indicated that mutual funds do not outperform passive benchmarks (e.g., Jensen, 1968; Ippolito, 1989; Sharpe, 1992; Elton et al., 1993; Malkiel, 1995; Chen et al., 2002). In contrast, other studies have shown evidence of persistence in performance (e.g., Grinblatt and Titman, 1992; Hendricks, Patel and Zeckhauser, 1993; Brown and Goetzmann, 1995; Elton, Gruber, and Blake, 1996; Ferreira et al., 2012). In particular, evidence exists of short-term persistence in fund performance. In addition, previous research has shown evidence that size, value, and fees affect the differences in fund performance (e.g., Brown and Goetzmann, 1997; Carhart, 1997), that is, fund performance worsens with fund size (Chen et al., 2004, Ferreira et al., 2012) and fees (Gil-Bazo and Ruiz-Verdu, 2009). Evidence also exists of a negative relationship between returns before fees and fees, and funds with low expected performance target "unsophisticated" investors because targeting such investors generates high distribution costs. In addition, evidence exists that underperforming funds with higher fees might incur elevated marketing costs because of their operations, which are then transferred to investors (Carhart, 1997; Christoffersen and Musto, 2002; Gil-Bazo and Ruiz-Verdu, 2009). Prior studies on fund flows, which are also built on the literature of mutual fee determinants (e.g., Sensoy, 2009; Gil-Bazo et al., 2009; Huang, Wei, and Yan, 2007; Barber et al., 2005; Nanda et al. 2005; Christoffersen and Musto, 2002; Jain and Wu, 2001; Sirri and Tufano, 1998; Chevalier et al., 1997; Gruber, 1996; Ippolito, 1992) have shown that money flows are positively related to performance after expenses and depend on fund size, age, and TER.

Although management style classification and contracts between investors and investment advisors have received significant attention in the literature, and most of them have been related to U.S. fund data,[5] little empirical research has comprehensively evaluated fund performance in emerging countries, especially when systematically gathered public information is absent.

To fill this gap, this thesis empirically studies the Colombian market, including i) the performance of investment funds and the style classification, ii) the link between management fees and performance among investment funds, and iii) the factors that may explain the differences in performance across these funds. These items are analyzed to understand whether i) investors have the right information to evaluate fund performance and ii) investment advisor compensation is determined according to performance or other determinants.

[5] See, for example, Ippolito (1989); Sharpe (1992); Brown and Goetzmann (1997); Coles, Suay, and Woodbury, (2000); Deli (2002); Elton, Gruber, and Blake (2003); Golec and Starks (2004); Chen et al. (2004); Farnsworth and Taylor (2006); Massa and Patgiri (2009); Gil-Bazo and Ruiz-Verdu (2009); Warner and Wu (2011)

To the best of our knowledge, this empirical study is the first to i) comprehensively collect all public and nonpublic data on investment funds' characteristics in Colombia, ii) systematically classify funds according to their management style, iii) study how management fees and fund performance are related in Colombia, and iv) analyze the cross-sectional determinants of fund performance.

A previous study on Colombia only focused on the trading behavior and performance of foreign investors using transaction records solely for equity stocks on the Colombian Stock Exchange (Pedraza, Pulga, and Vasquez, 2017).

We argue that these questions are relevant and worth investigating. First, by observing a different market, specifically in an emerging context such as Colombia, we contribute to the existing literature with "out-of-sample" evidence (i.e., outside the United States and other developed markets). In the context of less developed markets and institutions, this study, which analyzes investment funds in Colombia in an objective, consistent, and empirical manner, contributes to the existing literature as a basis for performance and measurement compensation. As Brown et al. (1997: page 374) point out, "objectivity is important because of moral hazard inherent in allowing managers and investment companies to self-report their styles without objective verification," and "consistency is needed for purposes of performance comparison." Further, this empirical evidence also contributes to the empirical evidence on optimal contracting in the delegated portfolio management industry in emerging countries.

Second, the local style classification and the public information on fund characteristics and returns do not convey any meaningful information about the strategies of advisory companies. Therefore, such a classification is useless for explaining differences in future returns among funds or identifying adequate benchmarks to evaluate past performance. Thus, the Colombian investment fund industry is missing an objective and rigorous empirical evaluation of the risk-adjusted performance of investment funds. Our study contributes to filling this gap, which should be of interest for both advisory companies (vis-à-vis their performance evaluation and compensation) and, obviously, investors.

This study also assists in understanding in the emerging markets context whether the failure to explicitly incorporate one or more indices for other types of fixed income, debt, or equity instruments in the analysis can affect the interpretation of investment fund performance results and develops appropriate performance evaluation models for investment funds (e.g., Sharpe, 1992; Blake et al., 1993; Brown and Goetzmann, 1997).

Third, we seek to identify the additional information that may be relevant for investors to properly assess fund performance and, thus, offer the Colombia regulator useful recommendations on the fund management characteristics and variables should be mandatorily disclosed and the best way to do so.

The relationship mentioned in the preceding paragraphs is examined using a sample of 183 investment funds in Colombia between 2009 and 2015. The unit of analysis is the contract governing the relationship between the investor and the investment advisor. This unique dataset provides an ideal test setting in which to analyze the style classification and to examine the factors that explain performance across funds in Colombia and the relationship between performance and fees.

The Colombian data are comprehensive, allowing us to analyze interesting hypotheses and avoid a number of pitfalls. To study this relationship, we construct a unique and rich dataset of fund characteristics, including fund size, age, various fees, measures of trading activity, and standard attributes such as lagged performance. We also hand collected data on all funds managed by trust companies ("*fiduciarias*") that represent an average of 80% of the Colombian market. To the best of our knowledge, these trust companies have rarely been jointly studied in the previous literature. Consistent with previous research, U.S. funds are much larger than others throughout the world, and the U.S. fund industry is older and more developed (Ferreira et al., 2012). Thus, reasons exist to believe that there is ample room to improve the identification of the determinants of investment fund performance in the Colombian investment fund industry.

We use a quadratic constrained regression algorithm employed by Sharpe (1992) to classify investment funds and measure risk-adjusted performance. We also use a return-based style classification algorithm consistent with asset pricing models and employed by Brown and Goetzmann (1997) to group funds based on the cross-sectional time series of past returns. These procedures allow us to explain differences in future returns among funds and consider several alternatives, including useful benchmark-adjusted returns for evaluating relative past performance. Li and Tiwari (2009) show that the optimal benchmark choice should reflect the manager's investment style. Garleanu, Panageas and Yu (2017) show that a relative performance evaluation with respect to a style index is optimal. Both studies offer a microfoundation of the alphas estimated following the style analysis of Sharpe (1992) that we use in this thesis.

Given the absence of a more detail style classification by the regulator and advisory companies, we immersed ourselves in legal prospectuses and technical reports to understand in greater detail their investment policy, the asset classes, and some characteristics of investment funds to complement the classification made by the regulator and to obtain more information on the common attributes of investment funds. The advantage that we obtain through this approach allows us to i) classify the investment funds based on a basic description and compare it with the classification by the regulator, ii) identify the appropriate broad indices as major asset classes, and iii) extract from the technical reports the portfolio fund composition classified by type of income or security. Although portfolio funds' composition by type of income described in the technical reports are not exactly the portfolio holdings of investment funds in Colombia (Grinblatt and Titman, 1993)—because advisory companies are not obliged to report such information—we do believe that these data represent a good approximation for inferring a broad asset class that is underlined from this type of income.

In addition, following Gil-Bazo et al. (2009), we focus on contract incentives as a function of fee rates to measure the relationship between before-fee risk-adjusted expected returns and fees. These fee rates are based on both the total assets managed by funds and funds' performance. Following Christoffersen and Musto (2002) and Gil-Bazo and Verdu (2009), we estimate the relationship between fund fees flow-to-performance sensitivity and performance, controlling for fund characteristics, to investigate how fund characteristics might affect a fund's compensation fee from 2009 to 2015. This measure captures a fund's return and fees based on the observable structure portfolio of the funds.

Finally, following Ferreira et al. (2012), we relate monthly fund performance, fund characteristics, and manager characteristics, when available, to investigate how fund characteristics might affect a fund's performance from 2009 to 2015.

We offer a comprehensive description of a return-based style analysis, document the management fee patterns for investment companies, and investigate how incentives are related to performance. We also compare one fund to another, as well as the time-series variations, to examine how contracts change over time. The results show systematic patterns that are broadly consistent with the theoretical predictions.

The empirical style classification that we followed identifies five major types of fund strategies. Consistent with previous research, the fund strategies may not exhaust the range of different fund managers but do provide an overview of the strategies that differentiate managers or advisory companies (Brown et al., 1997). In this sense, we find that investment funds in Colombia managed by trust companies ("*fiduciarias*") broadly fall into some familiar and not so familiar patterns of behavior based on the local style classification. The familiar patterns include equity funds and money market funds. However, we also identified that some of them fall into different categories based on the procedure that we followed. The unfamiliar pattern identified consists of more than two-thirds of the total number of investment funds investigated being categorized as money market funds. This result illustrates that most funds in Colombia behave similar to passive portfolios (money market assets), suggesting that the funds investigated are not widely diversified and lack specialization. Our results are also consistent with previous research because they provide useful means for identifying widespread fund strategies and common characteristics in investment funds (Brown et al., 1997, Chen et al., 2002, Ferreira et al., 2012). These findings contribute to the extant finance literature and indicate that investment funds in emerging markets can be categorized under this empirical style of classification, which is consistent with commonly used asset pricing models. As Brown et al. (1997) point out, the advantage of using this method over a heuristic classification is that researchers can use it to decompose styles into more familiar measures, such as time-varying factor loadings and risk premiums.

Our findings show that given the absence of industry classification for investment funds in Colombia and that the information provided to investors is too generic, the local classification provided by either the company advisory or even the regulator evidently has relatively little power to explain differential fund performance.

The major advantage gained by estimating positive and constrained coefficients on prespecified factors (Sharpe, 1992) is that they provide us some insights into the composition and behavior categories (Brown and Goetzmann, 1997), especially when no publicly useful benchmarks exist for evaluating relative past performance for investment funds and when a portfolio fund's composition is not reported or is too generic. When the loadings are not constrained to be positive, our results are consistence with prior research because we find no evident advantage in terms of explanatory value. The disadvantage that we find is when loadings on correlated indices might have collinearity issues—in this case, the loadings will be estimated with inaccuracy.

Our findings continue to show evidence that the quadratic constrained regression algorithm remains an effective analytical tool for creating relevant and informative benchmarks to assess the asset allocation in investment funds' choices because this tool provides a consistent view of investment decisions made by managers on behalf of investors (Sharpe, 1992). This style of analysis can serve as a valuable method to help investors achieve their goals in a cost-effective manner (Sharpe, 1992 page: 26; Brown et al., 1997; Chan, Chen, Lakanishok, 2002; Ben Dor, Jagannathan, 2002; Li and Tiwari 2009).

We show that the positive constraints in Sharpe (1992) are useful (Brown et al., 1997; Garleanu, Panageas and Yu, 2017) because they allow the coefficients to be interpreted as vector portfolio weights on investable indices. In addition, using the cluster algorithm is a complementary and useful procedure because using these tools together enables identification of common strategies among managers. The cluster algorithm analysis identifies aggregate behavior, and the Sharpe procedures assist in interpreting such behavior as a strategy (Sharpe, 1992; Brown et al., 1997).

We find that fund styles in Colombia generally do not deviate from a widely followed benchmark, and the customized benchmark based on Sharpe's weights is closely aligned with a fund's style. Colombian investment funds seemed to be averse to strategies involving the deep value of stock or equity because, as we have described, more than 90% of the investment funds investigated follow the money market's passive benchmarks. Viewed in this light, that most investment funds have historically underperformed the style benchmark (66% of the funds investigated), and some have outperformed market benchmarks (44%) but have provided an insignificant positive alpha may not be a complete surprise. Similar findings have been made about mutual funds in the U.S. market (Ippolito, 1989; Sharpe, 1992; Elton et al., 1993; Malkiel, 1995; Chen et al., 2002; Ferreira et al., 2012).

Our results show that no conclusive evidence exists to argue that advisory companies in Colombia are intentionally interested in manipulating prospectuses or technical reports to present higher alphas that result in more value added over a passive benchmark. Our findings also emphasize and support the need to have constructed—as a valuable supplement to other methods designed—a more robust benchmark return based on Sharpe weights for evaluating fund performance because it can provide a consistent view of investors' investment decisions (Sharpe, 1992; Garleanu, Panageas and Yu, 2017). The approximated benchmark return that we constructed based on portfolio weights reported in prospectuses and technical reports is less correlated with fund returns because the style fund classifications provided by the advisory companies in such technical reports might not be as precise as investors need, and they are noisier. This result is consistent with our hypothesis that investors in Colombia do not have enough, accurate, and timely information to evaluate fund performance in the Colombian market.

We also contribute to the existing literature on optimal contracting in the delegated portfolio management industry (Jensen and Meckling, 1976; Grinblatt and Timan, 1989; Guay, 1999; Ross, 2004; Massa et al., 2009) because our analysis of investment fund styles provides new evidence on the product offered by advisors in an emerging market, and we confirm that the manager's style choices in our market are more inclined by risk-averse and nonperformance considerations. The style dimensions we employed have been used in prior empirical research and are standard practice in the investment fund industry. The customized benchmarks computed and the methodology are useful descriptors of fund styles and performance.

Our results are also consistent with the self-interest from the manager's perspective because, as Chan et al. (2002: page 1422) point out, there is "more scope for money managers to follow their self-interest, with adverse consequences for portfolio performance." Thus, manager or company advisors play an important role in the investment fund industry in Colombia, and the evidence persists for nonperforming results. Several reasons may explain why investment funds managers in Colombia have some preference for money market assets. Investing in this type of asset generally results in good returns, and tilting toward these assets may appear to be safe from the standpoint of personal career risk. However, that some managers favor other strategy styles, such as equity or stocks with strong past performance, is probably not a complete surprise. Consistent with previous research, another reason might be the perception that value strategies take a long time to become profitable, whereas the money market style strategy and past winners at least have price momentum working in their favor over the intermediate term (Chen et al., 2002).

Another explanation for Colombian investment funds' tendency, which should be consistent with the theory (see Chen et al., 2002), is that managers or company advisors follow strategies that cannot be easily summarized by a single characteristic, such as equity, money markets, or past returns. Instead, managers or advisory companies may focus on many other security characteristics, and the result is a portfolio that does not deviate too much from a diversified benchmark index. Also possible is that managers or advisory companies realize that superior long-term results are unachievable or entail higher risk in an efficient or illiquid market. Hence, many do not deviate markedly from benchmarks.

We find that, on average, investment funds in Colombia have a positive relationship between risk-adjustment performance and fees; that is, funds that charge higher fees have a better performance before expenses but a worse performance after expenses. This finding is consistent with the result obtained when we include variables such as, size, age, and turnover, among others, that are likely—as posited by Gil-Bazo et al. (2009)—to assess the fund's costs related to performance. This positive relationship is consistent with the intuitive expectation that the value created for investors reflects the fee charged. However, observing this relationship by investment objectives based on our empirical style classification indicates mixed results. Money market and debt funds have a positive relation, whereas equity, balanced, or income funds have a negative relationship. This negative relationship is also consistent with prior research (see Gil-Bazo et al., 2009; Christoffersen and Musto, 2002), with some authors finding a negative relationship between performance and fees for equity and money market funds, respectively. One potential explanation for our results—as posited by Gil-Bazo et al. (2009)—is that fund performance might be positively related to fund total expenses because higher expenses might be synonymous with larger investments in research tools and higher salaries for "more talented managers," as is the case for funds classified in clusters 2 and 3. Moreover, investment funds with better performance tend to keep fees low—reflecting a negative relation—because of competition among other investment funds to attract money from "performance-sensitive investors" (Gil-Bazo et al., 2009: page 2179).

Our results are also consistent with previous studies (Christoffersen and Musto, 2002; Gil-Bazo et al. 2009) with respect to fund flows in investment fund industries. Although we do not find evidence to support the concept that flows are positively related to past performance, we find that a negative performance relative to the benchmark reduces flows, and relatively sophisticated investors in Colombia appear to penalize funds for poor performance (Sensoy, 2009). Moreover, we find evidence that flow-to-performance sensitivity decreases with fund age, and performance-sensitivity is positively associated with fund flow and flow-to-performance sensitivity. These results extend the findings of Gil-Bazo et al. (2009) and Christoffersen and Musto (2002) to non-U.S. funds because, although our findings are obtained for smaller samples funds, we present evidence that the elasticity of demand or performance-sensitivity for investment funds in Colombia appears to be an important determinant of fees. Investors who are highly sensitive to net performance are also sensitive to fees; thus, if investors' performance-sensitive increases, they would expect a decrease in fees.

We present evidence that low costs should be associated with better performance, which is consistent with previous research (Sensoy; 2009; Gil-Bazo et al., 2009; Huang, Wei, and Yan, 2007; Barber, Odean, and Zheng, 2005; Nanda, Wang, and Zheng, 2005; Jain and Wu, 2001; Sirri and Tufano, 1998; Chevalier and Ellison, 1997; Gruber, 1996; Ippolito, 1992). Economies of scale might reduce the operating costs for larger funds; thus, we show that a larger fund size is associated with lower fees. Although economies of learning might reduce operating costs for older funds if they could pass such learning on to investors in the form of lower fees, we do not find evidence of this argument because—in our case—older funds are associated with higher fees. However, higher expenses might be synonymous with larger investments in research tools and higher salaries for “more talented managers.” Thus, we find evidence that average fund performance is still positively related to a fund’s total expenses (Gil-Bazo et al. 2009). We do not find evidence to support the strategic argument—as posited by Christoffersen and Musto (2002)—that underperforming funds charge higher fees because, in our case, we do not find that higher fees translate into a large flow of money out of the fund.

We realize that other potential alternatives that we do not explicitly consider in our analysis, such as marketing fees, shareholder statements, and fund governance, among others, might exist that could explain the relationship between performance and fees. Although we believe that the sample used for these investigations is the most comprehensive dataset ever prepared to study investment fund performance in Colombia in terms of both number of funds and number of attributes, unfortunately, our data do not allow us to prevent all of these explanations. Thus, we believe that the ability to explain our findings might be limited.

In our investigation, we have encountered common determinants of investment fund performance according to previous research. However, we have also found some important differences. Our results extend the findings of research on investment fund performance determinants for non-U.S. funds, such as Ferreira et al. (2012) for non-U.S. funds; Dahlquist et al. (2000) for Swedish funds; and

Otten and Bams (2002) for U.K. funds. We find that, on average, fund size is positively related to performance, which is consistent with the findings in Ferreira et al. (2012) for non-U.S. funds. Moreover, we find that investment funds managed by large fund families show worse performance, confirming that when funds reach a certain size, economies of scale are "exhausted," thus eroding performance. This evidence is inconsistent with the findings in Ferreira et al. (2012) and some authors who studied U.S. funds. We find that, on average, back-end loaded investment funds in Colombia loads are positively related to performance because this condition dissuades redemption and acts in favor of performance given that the manager might hold more cash to invest in securities. We find strong evidence of this result for money market funds, which represent more than two-thirds of the funds in our sample. We also find that older equity and older debt funds perform better than younger funds, whereas younger money market funds performed better than older funds. We find evidence that is consistent with previous research that showed that closed-end funds in Colombia are positively related to performance (Coles et al., 2000; Khorana et al., 1999). We find evidence that money market funds' past performance has a positive effect on future performance but also find a nonsignificant effect of past performance on future performance for the rest of the investment objectives (clusters).

Our findings also indicate that the trading activity of Colombian investment funds is negatively related to performance. One explanation for this finding, which is consistent with previous research (Ferreira et al. 2012), is that the liquidity of the Colombian financial market might result in some disadvantages relative to more developed financial markets. More developed financial markets have higher liquidity than small markets, such as Colombia's; thus, higher transaction costs and, hence, lower performance result from lower liquidity. Our results are also consistent with the smart money hypothesis of Gruber (1996) because we find evidence that the flow of money for debt funds, balanced funds, and income funds is positively related to performance. We find no evidence that funds managed by teams perform worse than funds managed by a single person, as was shown in other studies (Ferreira et al., 2012; Massa, Reuter and Zitzewitz, 2010; Chen et al., 2004; Stein, 2002; Aghion and Tirole, 1997). Conversely, we find that funds managed by a team might perform better or no differently than funds managed by a single manager. This evidence extends the finding in Bliss, Potter, and Schwarz (2008), who also find that funds managed by a team perform no differently than funds managed by a single manager.

Finally, we find no significant difference between the results of the performance of investment fund determinants obtained by our benchmark Sharpe regression model and the benchmark prospectus model. Thus, no conclusive evidence exists that shows that advisory companies in Colombia are interested in intentionally manipulating prospectuses or technical reports to provide a different view of their management activities. However, we realize that all of the information needed to provide a consistent view of investment decisions in the investment fund industry in Colombia is not systematically collected by the regulator or the advisory company, leaving this dispendious task to investors. Therefore, our findings support our hypothesis that investors in Colombia do not have adequate, readily available, and accurate information to evaluate fund performance in the Colombian market.

The implications of our results are broad. A return-based classification system employed in this thesis can be used for investment funds in emerging markets to decompose styles into more familiar measures, such as time-varying factor loadings and risk premiums, as argued by Brown et al. (1997). The style analysis and the empirical style classification can serve as valuable methods to assist investors in achieving their goals in cost-effective ways. Our study offers a micro-foundation of the alphas estimated following the style analysis of Sharpe (1992). From the perspective of researchers interested in understating investment fund behavior in emerging markets, this study incorporates a compelling, systematic procedure that allows us to check whether differences in style are associated with differences in performance. From a managerial perspective, this study suggests to investors seeking opportunities to diversify their portfolios in emerging markets, particularly Colombia, guidelines that could be useful in understanding the problems faced by this type of investment, and maintaining the alignment of interests without affecting the performance and execution of the contract. This analysis will also help governments and regulators formulate their policies that rule these transactions because the effect of incentives on risk-adjusted performance should have important policy implications.

The remainder of this document is organized as follows. Section III provides a description of the theoretical framework that underlies the investment fund industry. Section IV provides a description of the sample data construction and all of the variables. In Section V, we present our empirical methodology and findings associated with style classification and identification of benchmarks to determine fund risk-adjusted performance as the basis for performance measurement and comparison. In Section VI, we present our empirical findings related to panel and cross-section analyses of the determinants of mutual fund performance in Colombia. In Section VII, we present our empirical findings associated with the univariate relationship among before-fee, risk-adjusted expected returns, and fees. In Section VIII, we explain the relationship between fees and performance as analyzed in Section VII and present our empirical findings on how fund characteristics might affect a fund's compensation fee. In Section IX, we present our empirical findings on how fund characteristics might determine investment fund performance in Colombia. In Section X, we offer our conclusions.

2. INTRODUCCIÓN (Spanish Version)

La distribución de la riqueza entre los inversionistas, las compañías inversionistas y los gerentes de portafolios en la industria de los fondos de inversión debe revestir un interés considerable para los investigadores y los profesionales dado los aspectos de agencia que surgen cuando los inversionistas delegan la gestión de los portafolios de inversión a terceros (v.g., compañías de inversión y gerentes de portafolios). Además, los inversionistas muestran un interés creciente en la selección de los fondos de inversión, exigiendo información y asesoramiento detallados al respecto.

Las compañías administradoras de fondos y los gerentes de portafolio desempeñan un papel crucial en las actividades de administración de portafolio pues ellos realizan actividades de investigación y toman decisiones de inversión en nombre de los inversionistas (Baumol et al., 1990). Los inversionistas tienen un interés obvio en evaluar el rendimiento de sus portafolios (Dahlquist et al., 2000). La gestión delegada de portafolios es, sin lugar a duda, uno de los conflictos de agencia más importantes que intervienen en la economía, con un impacto potencial en los mercados financieros y el desarrollo económico a nivel macro (Stracca, 2006).

El crecimiento de la industria de los fondos de inversión (o “mutual funds” en inglés) se inició en Estados Unidos, tal como señalan Ferreira et al. (2012). Dado que la industria de los fondos de inversión desempeña un papel importante en el desarrollo de los mercados financieros, el aumento de las inversiones en estos fondos se ha extendido de forma generalizada a otros países, incluyendo los mercados emergentes (Khorana, Servaes, y Tufano, 2005). Por ejemplo, Ferreira et al. (2012) indican que los activos bajo gestión fuera de Estado Unidos pasaron de un 38 % en 1997 a un 54 % de los activos totales en 2007. Tal crecimiento no es una excepción en el contexto colombiano. El interés público en la industria colombiana de fondos de inversión ha ido en rápido aumento. Para finales de 2015, la industria de fondos de inversión en Colombia gestionaba activos financieros por valor de más de COP 56 billones (USD$17.500 millones de dólares aproximadamente[6]), mientras que la cifra en 1999 era de COP 29.300 millones[7] (USD$9.200 millones de USD aproximadamente), lo que refleja un crecimiento del 92 % entre 1999 y 2015, aproximadamente un 6 % del PIB colombiano. Además, el número de fondos de inversión ha crecido dramáticamente, de 198 fondos que había en 2009 a 403 fondos para finales de 2015. Durante el año 2015, más del 71% de la industria de los fondos de inversión en Colombia está gestionada y controlada por Compañías Fiduciarias, mientras que el resto está en manos de Comisionistas de Bolsa. Las Fiduciarias se han mantenido como el tipo de administradora de fondos más representativa en el contexto colombiano con una gestión de activos superiores a COP 40.000 millones (USD 12.530 millones aproximadamente[8]).

Los fondos de inversión en Colombia están supervisados por la Superintendencia Financiera de Colombia (la SEC en Colombia). Mensualmente, la Superintendencia Financiera solo informa públicamente los retornos diarios de los

[6] Convertidos a USD con la tasa de conversión de COP a 31 de diciembre de, 2015 (1 USD equivale a 3,19168).
[7] Información extraída y analizada de la Superintendencia Financiera de Colombia.
[8] Convertidos a USD con la tasa de conversión de COP a 31 de diciembre de, 2015 (1 USD equivale a 3,19168).

fondos, los activos totales gestionados, el número de inversionistas, los flujos netos y una clasificación básica de estilos. Si los inversionistas quieren obtener y evaluar información con respecto a sus inversiones, en adición a la información disponible públicamente en la Superintendencia Financiera, deben recurrir a los informes técnicos emitidos por las compañías administradores de los fondos, es decir, a las fiduciarias o comisionistas de bolsa.

Aunque la industria de los fondos de inversión en Colombia ha registrado un fuerte impulso en términos de desarrollo y expansión, parte de esto favorecido por la normatividad local, la cual hasta cierto punto ha estado inspirada en Estados Unidos y algunos países europeos, aun existe un margen considerable de mejora para converger a los estándares de mercados más desarrollados. La experiencia y el mercado mismo han exigido mejoras necesarias para promulgar requerimientos más rigurosos de transparencia y claridad en la información dirigida a los inversionistas, pues en nuestro caso la información difundida públicamente por la Superintendencia Financiera, así como la información difundida por los administradores de los fondos en sus prospectos e informes técnicos, no está sistemáticamente organizada y de fácil acceso a los inversionistas para evaluar el rendimiento de sus inversiones. Además, la clasificación actual del estilo del fondo, el cual no está determinada objetivamente, no permite explicar los retornos de los fondos de manera diferenciada. No hay índices de referencia disponibles y el regulador no publica información acerca de las comisiones de los fondos de inversión o la compensación de los gestores, ni el tipo de activos invertidos en los portafolios.

Muchos autores han intentado explicar el desempeño de los fondos de inversión al emplear índices de referencia pasivos y diversas características de los fondos como determinantes potenciales del rendimiento futuro del fondo, tales como el tamaño del fondo, la edad, las comisiones fijas y los gastos, comisiones por salida o entrada, "turnover", los flujos y los retornos. [9]

Un debate importante en la literatura es i) si el diseño de las comisiones de gestión de los fondos de inversión está vinculado al rendimiento (p. ej., Jensen y Meckling, 1976; Grinblatt y Timan, 1989; Zajac y Westphal, 1994; Guay, 1999; Deli, 2002; Ross, 2004; Massa et al., 2009), ii) si tal diseño proporciona a los gestores los incentivos adecuados para alinear sus intereses (p.ej., Battacharya y Pfleiderer, 1985; Starks, 1987; Stoughton, 1993; Admati y Pfleiderer, 1997; Christoffersen y Musto, 2002; Gómez y Sharma, 2006; Gil-Bazo y Verdú, 2009; Dybvig, Farnsworth y Carpenter, 2010; Agarwal, Gómez, y Priestley, 2012), y iii) si los estilos de gestión están determinados objetiva y empíricamente para la medición y compensación del desempeño del fondo (p. ej., Sharpe, 1992; Brown y Goetzmann, 1997; Li y Tiwari, 2009; Garleanu, Panageas y Yu, 2017).

En la industria de los fondos de inversión, la clasificación por estilos y los objetivos de inversión se utilizan de forma generalizada para establecer las diferencias entre fondos de inversión (e.g., Sharpe, 1992; Brown y Goetzmann, 1997; Chen et al., 2002). Por cuestiones de agencia, es importante entender la clasificación de estilos de un fondo, dado que el comportamiento de los gestores

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[9] Ver por ejemplo, Jensen (1968); Grinblatt y Titman (1989a), Ippolito (1989); Carhart (1997); Sirri y Tufano (1998); Coles, Suay, y Woodbury, (2000); Deli (2002); Elton, Gruber, y Blake (2003); Golec y Starks (2004); Chen et al. (2004); Farnsworth y Taylor (2006); Massa y Patgiri (2009); Gil-Bazo y Ruiz-Verdu (2009); Warner y Wu (2011); (Ferreira et al., 2012).

de los fondos de inversión puede estar condicionado por consideraciones ajenas a la diversificación o la maximización de los retornos del portafolio (Chan et al., 2002).

Investigaciones previas han mostrado evidencia que los fondos de inversión no superan el rendimiento de los índices de referencia pasivos (p. ej., Jensen, 1968; Ippolito, 1989; Sharpe, 1992; Elton et al., 1993; Malkiel, 1995; Chen et al., 2002). En contraste con ello, otros estudios han mostrado evidencia de la persistencia en el desempeño del fondo (p. ej., Grinblatt and Titman, 1992; Hendricks, Patel and Zeckhauser, 1993; Brown and Goetzmann, 1995; Elton, Gruber, and Blake, 1996; Ferreira et al., 2012). Concretamente, existe evidencia de la persistencia a corto plazo en el rendimiento de los fondos. Además, las investigaciones previas ofrecen pruebas de que el tamaño, el valor y las comisiones afectan el rendimiento del fondo de una manera diferenciada (p. ej., Brown and Goetzmann, 1997; Carhart, 1997), esto es, el rendimiento del fondo se empeora con el tamaño del fondo (Chen et al., 2004, Ferreira et al., 2012) y con las comisiones (Gil-Bazo and Ruiz-Verdu, 2009). También existe evidencia de una relación negativa entre los retornos-antes de comisiones y las comisiones. Los fondos con un rendimiento estimado inferior buscan inversionistas “poco sofisticados” ya que al trabajar con tales inversionistas se generan unos costos de distribución elevados. Además, existe evidencia de que los fondos con un rendimiento bajo y comisiones elevadas pueden incurrir en costos de marketing elevados por causa de sus operaciones, que luego son trasladadas a los inversionistas (Carhart, 1997; Christoffersen and Musto, 2002; Gil-Bazo and Ruiz-Verdu, 2009). Estudios anteriores acerca de los flujos de los fondos, los cuales están basados también en la literatura de los determinantes de las comisiones en los fondos mutuos de inversión, (p. ej., Sensoy, 2009; Gil-Bazo et al., 2009; Huang, Wei, and Yan, 2007; Barber et al., 2005; Nanda et al. 2005; Christoffersen and Musto, 2002; Jain and Wu, 2001; Sirri and Tufano, 1998; Chevalier et al., 1997; Gruber, 1996; Ippolito, 1992) han demostrado que los flujos de recursos están relacionados positivamente con el rendimiento de los fondos después de costos y que a su vez dependen del tamaño, la edad y gastos totales (o “total expense ratio”-TER) del fondo.

Aunque la clasificación de estilos de gestión, y los contratos entre inversionistas y compañías administradoras de fondos han gozado de una atención significativa en la literatura financiera, y la mayor parte de ellos han estado relacionados con datos de fondos de EE. UU., [10] no ha habido mucha investigación empírica que haya evaluado exhaustivamente el rendimiento de los fondos en países emergentes, especialmente en ausencia de información pública disponible de forma sistemática.

Con el fin de llenar este vacío, la presente tesis estudia empíricamente en el mercado colombiano, i) el rendimiento de los fondos de inversión y la clasificación de estilos, ii) la relación entre las comisiones de gestión y el rendimiento de los fondos de inversión y iii) los factores que pueden explicar las diferencias de rendimiento entre estos fondos. Estos elementos son analizados para investigar si i) los inversionistas cuentan con la información apropiada para evaluar el

[10] Por ejemplo, Ippolito (1989); Sharpe (1992); Brown y Goetzmann (1997); Coles, Suay, y Woodbury, (2000); Deli (2002); Elton, Gruber, y Blake (2003); Golec y Starks (2004); Chen et al. (2004); Farnsworth y Taylor (2006); Massa y Patgiri (2009); Gil-Bazo y Ruiz-Verdu (2009); Warner y Wu (2011)

rendimiento de los fondos y si ii) la compensación del gestor del fondo de inversión es determina de acuerdo con el rendimiento u otros factores determinantes.

Entendemos que el presente estudio empírico es el primero en i) recopilar exhaustivamente todos los datos públicos y no públicos sobre las características de los fondos de inversión en Colombia, ii) clasificar sistemáticamente los fondos en función de su estilo de gestión, iii) estudiar la forma en que se relacionan las comisiones y el rendimiento de los fondos en Colombia, y iv) analizar de una manera cruzada ("cross-sectional") los determinantes del rendimiento de los fondos.

Un estudio anterior en Colombia se centró exclusivamente en la conducta y el rendimiento bursátil de los inversionistas extranjeros usando exclusivamente los registros de transacciones para acciones ("*equity funds")* en la bolsa de Colombia (Pedraza, Pulga, and Vasquez, 2017).

Consideramos que estos aspectos son relevantes y merecen ser investigados por las siguientes razones. En primer lugar, al observar un mercado diferente, concretamente en un contexto emergente como el de Colombia, contribuimos a la literatura existente con evidencia novedosa (esto es, fuera de Estados Unidos y otros mercados desarrollados). Es decir, en un contexto donde las instituciones y los mercados financieros son menos desarrollados, este estudio, el cual analiza los fondos de inversión en Colombia de forma objetiva, consistente y empírica, contribuye a la literatura existente como base para la medición del rendimiento y las compensaciones en fondos de inversión. Tal como señalan Brown et. al. (1997: página 374). "la objetividad es importante por el riesgo moral inherente en permitir a los gestores y las compañías de inversión auto-reportar sus propios estilos sin una verificación objetiva” y “es consistente por la necesidad de tener una coherencia a efectos de comparación del desempeño”. Además, esta evidencia empírica también contribuye a fortalecer la evidencia empeрica relacionada con la realización optima de contratos en la industria delegada de gestión de portafolios de inversión en países emergentes.

En segundo lugar, la clasificación local de estilos y la información pública acerca de las características y los retornos de los fondos no ofrecen ningún tipo de información valiosa acerca de las estrategias de las compañías administradoras de los fondos. Por tanto, tal clasificación es inútil a efectos de explicar las diferencias en los retornos futuros entre fondos o para identificar los índices de referencia adecuados para evaluar el rendimiento histórico. Así, la industria de fondos de inversión en Colombia carece de una evaluación empírica objetiva y rigurosa del rendimiento ajustado al riesgo de los fondos de inversión. Nuestro estudio contribuye a llenar este vacío, el cual debería ser de interés tanto para las compañías administradoras de fondos de inversión (a efectos de comparar la evaluación del rendimiento y la compensación), como para los inversionistas, obviamente.

El presente estudio también ayuda a entender, en el contexto de los mercados emergentes, si la incapacidad de incorporar en el análisis explícitamente uno o más índices asociados a activos de renta fija, deuda o instrumentos de equity, puede afectar a la interpretación de los resultados del rendimiento de los fondos de inversión y ayuda a desarrollar modelos apropiados de evaluación del rendimiento para los fondos de inversión (v.g., Sharpe, 1992; Blake et al., 1993; Brown and Goetzmann, 1997).

En tercer lugar, buscamos identificar información adicional que pueda ser relevante para los inversionistas a efectos de evaluar adecuadamente el rendimiento de los fondos y, de tal forma, ofrecer recomendaciones útiles al regulador en Colombian en lo concerniente a las características y atributos de la gestión de fondos que deberían ser revelados obligatoriamente, así como la mejor forma de hacerlo.

La relación mencionada en los párrafos anteriores es examinada usando una muestra de 183 fondos de inversión en Colombia entre los años de 2009 a 2015. La unidad de análisis es el contrato que gobierna la relación entre el inversionista y la compañía gestora del fondo de inversión. Este conjunto de datos único proporciona un contexto de prueba idóneo para analizar la clasificación de estilos, y examinar los factores que explican el rendimiento entre fondos en Colombia y la relación entre el rendimiento y las comisiones.

Los datos obtenidos en Colombia son exhaustivos, lo que nos permite analizar hipótesis de interés y evitar una serie de errores potenciales. Para estudiar esta relación, construimos una base de datos única y rica en información acerca de las características de los fondos, entre las que se incluyen el tamaño, la edad, las diversas comisiones, mediciones de actividad y otros atributos estándar como el rezago de los rendimientos. También recopilamos manualmente datos de todos los fondos gestionados por las compañías fiduciarias, las cuales representan en promedio el 80 % del mercado colombiano. Hasta donde sabemos, la literatura previa no ha estudiado de manera completa los fondos de inversión en Colombia. Tal y como se ha mencionado en investigaciones previas, los fondos de EE. UU. son mucho más grandes que los del resto del mundo, y la industria de fondos de inversión en EE. UU. cuenta con mayor trayectoria y es más desarrollada (Ferreira et al., 2012). De este modo, existen razones para creer que hay un margen de mejora considerable para la identificación de los determinantes del rendimiento de los fondos en la industria de los fondos de inversión en Colombia.

Usamos un algoritmo cuadrático de regresión restringida empleado por Sharpe (1992) para clasificar los fondos de inversión y medir el rendimiento ajustado al riesgo. Igualmente usamos un algoritmo de clasificación de estilos basado en retornos, consistente con los modelos de valoración de activos de portafolio y empleado por Brown y Goetzmann (1977) para agrupar por “cluster” fondos en base a la serie temporal de la sección cruzada de retornos históricos. Estos procedimientos nos permiten explicar las diferencias en los retornos futuros entre fondos y considerar diversas alternativas, incluyendo índices de referencia útiles ajustados a riesgos para evaluar el rendimiento histórico relativo. Li y Tiwari (2009) muestran que la elección óptima del índice de referencia debería reflejar el estilo de inversión del gerente del portafolio. Garleanu, Panageas y Yu (2017) muestran que una evaluación de rendimiento relativo con respecto a un índice de estilo es óptima. Ambos estudios ofrecen un microfundamento de las alfas estimadas siguiendo el análisis de estilo de Sharpe (1992) empleado en esta tesis.

En vista de la ausencia de una clasificación de estilo más detallada por parte del regulador y los administradores de los fondos, nos sumergimos en los prospectos legales y los informes técnicos de los fondos para entender de manera más detallada su política de inversión, las clases de activos y algunas características de los fondos de inversión para complementar la clasificación realizada por el regulador, así como para obtener más información acerca de los atributos comunes de los fondos de inversión. La ventaja que obtenemos de este enfoque nos permite i) clasificar los fondos de inversión basándonos en una descripción básica y compararla con la clasificación llevada a cabo por el regulador, ii) identificar los índices generales apropiados como clases de activos principales, y iii) extraer de los informes técnicos la composición de los activos de los portafolios clasificados por tipo de renta o título. Si bien la composición de los portafolios de los fondos por tipo de renta que se describe en los informes técnicos no equivale exactamente al detalle de los tipos de activos invertidos en el portafolio de los fondos de inversión en Colombia (Grinblatt and Titman, 1993) —debido a que los administrador de fondos no están obligadas a ofrecer tal información— sí creemos que esos datos representan una buena aproximación para inferir una clase de activos general sustentada a este tipo de rentas.

Además, siguiendo Gil-Bazo et al. (2009), nos centramos en los incentivos contractuales como una función de las tasas de comisiones para medir la relación entre los retornos esperados ajustados al riesgo antes de comisiones y las comisiones per se. Las comisiones están basadas tanto en el total de los activos gestionados por los fondos como en el rendimiento obtenido de los mismos. Siguiendo Christoffersen y Musto (2002), y Gil-Bazo y Verdu (2009), estimamos la relación entre la sensibilidad al “flujo a rendimiento” de las comisiones de los fondos y el rendimiento, controlando las características de los fondos, para investigar de qué forma las características de éstos pueden afectar la comisión de compensación del fondo entre 2009 y 2015. Esta medición captura el retorno y las comisiones a partir de la estructura observable del portafolio del fondo.

Por último, basándonos en Ferreira et al. (2012), relacionamos el rendimiento mensual de los fondos, las características de los fondos y las de los gestores, cuando están disponibles, para investigar cómo las características del fondo pueden afectar al rendimiento de éste entre 2009 y 2015.

Ofrecemos una descripción exhaustiva del análisis de estilo basado en retornos, documentamos los patrones de las comisiones de gestión para las compañías administradoras de los fondos e investigamos de qué forma los incentivos están vinculados al rendimiento. También comparamos un fondo con otro, así como las variaciones en la serie cronológica, para examinar la forma en que cambian los contratos a lo largo del tiempo. Los resultados muestran patrones sistemáticos ampliamente consistentes con las predicciones teóricas.

La clasificación de estilos empírica que hemos seguido identifica cinco estrategias básicas de fondos. Consistente con investigaciones previas, es posible que las estrategias de los fondos identificados no cubran toda la gama de diferentes gestores de fondos, pero sí ofrecen una visión general de las diferentes estrategias usadas por los gerentes de portafolio o gestores de los fondos de inversión en Colombia (Brown et al., 1997). En este sentido, observamos que los fondos de inversión en Colombia gestionados por fiduciarias suelen encajar en algunos patrones de conducta familiares, y otros no tanto, basados en nuestra clasificación local de estilos. Los patrones familiares incluyen los fondos de "*equity*" y los fondos de "*money market*". No obstante, también hemos identificado que algunos de ellos encajan en categorías distintas en función del procedimiento seguido. El patrón no familiar identificado consiste en que más de dos tercios del total de los fondos de inversión investigados se caracterizan como fondos de "*money market"* o corto plazo. Este resultado muestra que la mayoría de los fondos de Colombia se comportan de forma similar a portafolios pasivos (activos de *money market*), lo que indica que los fondos investigados no están muy diversificados y carecen de especialización. Nuestros resultados son consistentes con investigaciones previas, ya que nuestro procedimiento ofrece un medio útil para identificar estrategias de fondos generalizadas y características comunes en los fondos de inversión (Brown et al., 1997, Chen et al., 2002, Ferreira et al., 2012). Estos hallazgos contribuyen a la literatura financiera existente e indican que los fondos de inversión de mercados emergentes también pueden categorizarse bajo esta clasificación de estilos empírica, la cual es consistente con los modelos de valoración de los activos de portafolios empleados habitualmente. Tal como señalan Brown et al. (1997), la ventaja de utilizar este método sobre una clasificación heurística es que los investigadores pueden utilizarlo para desglosar estilos en mediciones más familiares, tales como los coeficientes condicionales y las primas de riesgo.

Nuestros hallazgos muestran que, dada la ausencia de una clasificación de industria para los fondos de inversión en Colombia y que la información proporcionada a los inversionistas es demasiado genérica, la clasificación local ofrecida por las compañías administradoras de los fondos e incluso la ofrecida por el regulador, obviamente, tiene una capacidad relativamente reducida de explicar el rendimiento de los fondos de una manera diferenciada.

La principal ventaja obtenida al estimar coeficientes positivos y restringidos sobre los betas pre-especificados de la regresión (Sharpe, 1992) es que nos ofrecen algunas pistas acerca de la composición y las categorías de comportamiento del fondo (Brown y Goetzmann, 1997), especialmente cuando no existen índices de referencia útiles para evaluar el rendimiento relativo histórico de los fondos y cuando no se informa la composición de los activos del portafolio o la información es demasiado genérica. Cuando los betas o factores de la regresión no se restringen a ser positivas, nuestros resultados son consistentes con investigaciones previas, debido a que no encontramos una ventaja evidente en términos del valor explicativo. Le desventaja que advertimos es cuando los betas o factores de la regresión están correlacionados con otros índices o factores, los cuales pueden tener problemas de colinealidad; en este caso, los pesos se estiman de forma inexacta.

Nuestros hallazgos continúan dando muestras de que el algoritmo cuadrático de regresión restringida sigue siendo una herramienta de análisis eficaz para la creación de índices de referencia relevantes e informativos que permitan evaluar la asignación de activos en las elecciones del portafolio de inversión, dado que esta herramienta proporciona una visión homogénea de las decisiones de inversión realizadas por los gerentes del portafolio en representación de los inversionistas (Sharpe, 1992). Este estilo de análisis puede servir como un método valioso para ayudar a los inversionistas a analizar sus inversiones y alcanzar sus objetivos de forma más eficiente (Sharpe, 1992 page: 26; Brown et al., 1997; Chan, Chen, Lakanishok, 2002; Ben Dor, Jagannathan, 2002; Li and Tiwari 2009).

Mostramos que las restricciones positivas en Sharpe (1992) son útiles (Brown et al., 1997; Garleanu, Panageas and Yu, 2017) porque permiten que los coeficientes se interpreten como un vector del peso del portafolio sobre índices invertibles. Además, emplear el algoritmo de “cluster” o conglomerado es un procedimiento complementario y útil dado que utilizar estas herramientas conjuntamente permite la identificación de estrategias comunes entre gestores. El análisis de algoritmo de “cluster” identifica el comportamiento de los fondos de manera agrupada, y el procedimiento establecido por Sharpe ayuda a interpretar tal comportamiento como una estrategia (Sharpe, 1992; Brown et al., 1997).

Comprobamos que los estilos de los fondos en Colombia no suelen desviarse del índice de referencia comúnmente seguido, y el índice de referencia personalizado basado en las ponderaciones de Sharpe está estrechamente alienado con el estilo de un fondo. Los fondos de inversión colombianos parecen reacios a las estrategias que impliquen una profundidad en los fondos de acciones o “equity” debido a que, tal como hemos descrito, más del 90 % de los fondos de inversión investigados siguen los índices de referencia pasivos de *money markets*. Visto de esta manera, el hecho de que la mayoría de los fondos de inversión hayan tenido históricamente un rendimiento inferior al índice de referencia de estilo (66% de los fondos investigados) y que algunos hayan superado el rendimiento de los índices de referencia del mercado (44 %) pero hayan ofrecido un alfa positivo insignificante, no debería resultar del todo sorprendente. Hechos similares se han encontrado con respecto a los fondos de inversión en el mercado estadounidense (Ippolito, 1989; Sharpe, 1992; Elton et al., 1993; Malkiel, 1995; Chen et al., 2002; Ferreira et al., 2012).

Nuestros resultados muestran que no existen evidencias concluyentes que permitan argumentar que las compañías administradoras de los fondos en Colombia estén interesadas deliberadamente en manipular los prospectos o los informes técnicos para presentar alfas más elevados que conlleven a mostrar un mayor valor agregado con respecto al índice de referencia pasivo. Nuestros hallazgos también refuerzan y apoyan la necesidad que tuvimos de haber construido —como un complemento valioso para los otros métodos designados— un índice de referencia ("benchmark") robusto basado en las ponderaciones de Sharpe para evaluar el rendimiento de los fondos, ya que éste proporciona una visión homogénea de las decisiones de inversión por parte de los inversionistas (Sharpe, 1992; Garleanu, Panageas and Yu, 2017). El retorno aproximado del índice de referencia que hemos construido a partir de las ponderaciones de portafolio incluidas en los prospectos y los informes técnicos está menos correlacionado con los retornos del fondo debido a que las clasificaciones de estilo de los fondos proporcionadas por las compañías administradoras de los fondos en los informes técnicos podrían no ser tan precisas como necesitan los inversionistas, además de incluir más variabilidad. Este resultado es consistente con nuestra hipótesis de que los inversionistas en Colombia no cuentan con información suficiente, precisa y puntual para evaluar el rendimiento de los fondos en el mercado colombiano.

También contribuimos a la literatura existente acerca del desarrollo óptimo de contratos en la industria de la gestión delegada de portafolios (Jensen and Meckling, 1976; Grinblatt and Timan, 1989; Guay, 1999; Ross, 2004; Massa et al., 2009) debido a que nuestro análisis de los estilos de fondos de inversión proporciona nuevas evidencias con respecto al producto ofrecido por las compañías administradoras de fondos en un mercado emergente, y confirmamos que las elecciones de estilo del gestor en nuestro mercado están más inclinadas hacia consideraciones a versas al riesgo y de bajo desempeño. Las dimensiones de estilo que hemos empleado también han sido utilizadas en investigaciones previas y han sido una práctica estándar en la industria de los fondos de inversión. Los índices de referencia calculados en este trabajo y la metodología empleada son descriptores útiles de los estilos y el rendimiento de los fondos.

Nuestros resultados también son consistentes con el interés propio desde la perspectiva del gestor porque, tal como señalan Chan et al. (2002: página 1422) "existe un mayor margen para que los gestores de dinero sigan su propio interés con consecuencias adversas para el rendimiento del portafolio". Así, el gestor o las compañías administradoras de los fondos desempeñan un papel importante en la industria de los fondos de inversión en Colombia y sigue habiendo pruebas del bajo desempeño de los fondos. Hay varios motivos que pueden explicar por qué los gestores de fondos de inversión en Colombia muestran cierta preferencia por los activos de *money markets*. Invertir en este tipo de activo suele ofrecer buenos retornos, e inclinarse por este tipo de activos puede parecer seguro desde la perspectiva de los riesgos para la carrera personal. No obstante, algunos gestores se decantan por otros estilos estratégicos, tales como acciones o "*equity"* con un fuerte rendimiento histórico, lo cual probablemente no resulte una gran sorpresa. Consistente con investigaciones previas, otro motivo podría ser la percepción de que las estrategias de valor necesitan bastante tiempo para alcanzar la rentabilidad, mientras que las estrategias de estilo de *money market* y las de replicar aquellas de rendimientos consistentes, como mínimo tienen la inercia del momento jugando a su favor en el medio plazo (Chen et al., 2002).

Otra explicación de la tendencia de los fondos de inversión en Colombia, que debería ser consistente con la teoría (ver Chen et al., 2002), es que los gestores o las compañías administradoras de fondos siguen estrategias que no se pueden reducir fácilmente a una sola característica, como puede ser inversiones en acciones (“*equity”)*, “*money market” o* retornos históricos. En lugar de ello, los gestores de fondos pueden centrarse en otras características de activos, y el resultado es un portafolio que no se desvía demasiado de un índice de referencia diversificado. También es posible que los gestores o las compañías administradoras de fondos consideren que obtener resultados superiores en el largo plazo es difícil de conseguir o conllevan un mayor riesgo en un mercado ineficiente o ilíquido. Es por eso, que muchos fondos en Colombia no se desvían de los índices de referencia significativamente.

Encontramos que, en promedio, los fondos de inversión en Colombia mantienen una relación positiva entre el rendimiento ajustado al riesgo y las comisiones; esto es, que los fondos que cobran comisiones mayores tienen un rendimiento superior antes de gastos, pero un rendimiento peor después de éstos. Este hallazgo es consistente con el resultado obtenido cuando incluimos variables como el tamaño, la edad y el “turnover”, entre otros, los cuales permiten—tal como plantean Gil-Bazo et al. (2009)— evaluar los costos del fondo con respecto a su rendimiento. Esta relación positiva está acorde con la expectativa intuitiva de que el valor creado para los inversionistas refleje la comisión cobrada. No obstante, al observar esta relación por objetivos de inversión, basándonos en nuestra clasificación empírica de estilos, encontramos resultados mixtos. Los fondos de "*money market"* y deuda tienen una relación positiva, mientras que los fondos de "*equity"*, balanceados o de renta tienen una relación negativa. Esta relación negativa también es consistente con investigaciones previas (ver Gil-Bazo et al., 2009; Christoffersen y Musto, 2002), pues algunos autores encontraron una relación negativa entre el rendimiento y las comisiones por fondos de *equity* y *money market*, respectivamente. Una posible explicación de nuestros resultados—tal como plantean Gil-Bazo et al. (2009)— es que el rendimiento de los fondos puede estar relacionado positivamente con los gastos totales de los fondos, dado que unos gastos más elevados pueden ser sinónimo de mayores inversiones en herramientas de investigación y salarios más elevados para "gerentes de portafolio con más talento", tal como es el caso de los fondos clasificados en los grupos 2 y 3. Además, los fondos de inversión con un rendimiento mayor tienden a mantener unas comisiones bajas —lo que refleja una relación negativa— debido a la competencia entre estos fondos de inversión para atraer dinero de "inversionistas sensibles al rendimiento" (Gil-Bazo et al., 2009: página 2179).

Nuestros resultados también son consistentes con estudios anteriores (Christoffersen y Musto, 2002; Gil-Bazo et al. 2009) en lo que respecta al flujo de los fondos en la industria de los fondos de inversión. Aunque no encontramos evidencia para respaldar la idea de que los flujos están relacionados positivamente con el rendimiento histórico, observamos que un rendimiento negativo con respecto al índice de referencia reduce los flujos, y que los inversionistas relativamente sofisticados en Colombia parecen penalizar a los fondos con un rendimiento pobre (Sensoy, 2009). Es más, encontramos evidencia que la sensibilidad al flujo con respecto al rendimiento se reduce con la edad del fondo, y que la sensibilidad al rendimiento esta asociada positivamente con el flujo del fondo y con la sensibilidad al flujo con respecto al rendimiento. Estos resultados amplían la evidencia obtenida por Gil-Bazo et al. (2009) y Christoffersen y Musto (2002) con respecto a los fondos no estadounidenses, dado que, a pesar de que nuestros hallazgos son obtenidos de una muestra de fondos más reducidas, presentamos evidencia que la elasticidad de la demanda o la sensibilidad al rendimiento de los fondos de inversión en Colombia parece ser un determinante importante para las comisiones. Los inversionistas que son muy sensibles al rendimiento neto son también muy sensibles a las comisiones; así, si aumenta la sensibilidad de los inversionistas al rendimiento, esperarán una reducción en las comisiones.

Presentamos evidencia que unos costos bajos deberían estar asociados con un mejor rendimiento, lo que es consistente con investigaciones previas (Sensoy; 2009; Gil-Bazo et al., 2009; Huang, Wei, y Yan, 2007; Barber, Odean, y Zheng, 2005; Nanda, Wang, y Zheng, 2005; Jain y Wu, 2001; Sirri y Tufano, 1998; Chevalier y Ellison, 1997; Gruber, 1996; Ippolito, 1992). Las economías de escala pueden reducir los costos operativos de los fondos que tienen un mayor tamaño; así, mostramos que un mayor tamaño del fondo va asociado a unas comisiones menores. Aunque las economías del conocimiento pueden reducir los costos operativos en el caso de los fondos más antiguos, y éstos pueden trasladar tal conocimiento a los inversionistas en forma de comisiones más reducidas, no encontramos evidencia en los fondos en Colombia que respalden tal argumento, dado que, en nuestro caso, los fondos más antiguos están asociados con comisiones más elevadas. No obstante, unos gastos más elevados pueden ser sinónimo de inversiones mayores en herramientas de investigación y salarios más elevados para “gerente de portafolio con más talento”. Por tanto, encontramos evidencia que el rendimiento promedio de un fondo sigue estando positivamente relacionado con los gastos totales de un fondo (Gil-Bazo et al. 2009). No encontramos evidencia que respalden el argumento estratégico —tal como plantean Christoffersen y Musto (2002)— de que los fondos con un rendimiento menor cobren comisiones más elevadas dado que, en nuestro caso, no observamos que las comisiones más elevadas se traduzcan en un gran flujo de dinero que salga del fondo.

Somos conscientes que existen otras posibles alternativas que no consideramos explícitamente en nuestro análisis, tales como los costos de marketing, las declaraciones de accionistas y la información del gobierno de los fondos, entre otras, que puedan explicar la relación entre el rendimiento y las comisiones. Aunque creemos que la muestra empleada para estas investigaciones es el conjunto de datos más exhaustivo que jamás se haya recopilado para estudiar el rendimiento de los fondos de inversión en Colombia, tanto en términos de número de fondos como de atributos, nuestros datos no nos permiten prever todas esas explicaciones. Por ello creemos que la capacidad de explicar nuestros hallazgos puede ser limitada.

En nuestra investigación hemos encontrado determinantes comunes del rendimiento de los fondos de inversión consistente con estudios previos. No obstante, también hemos detectado algunas diferencias considerables. Nuestros resultados amplían los hallazgos de la investigación acerca de los determinantes del rendimiento de los fondos de inversión para los fondos no estadounidenses, tal como Ferreira et al. (2012) para fondos no estadounidenses; Dahlquist et al. (2000) para fondos suecos; y Otten y Bams (2002) para fondos británicos. Es más, comprobamos que los fondos de inversión gestionados por grandes familias de fondos muestran un rendimiento peor, lo que confirma que, al alcanzar un cierto tamaño, las economías de escala se "agotan", lo que deteriora el rendimiento. Esta evidencia discrepa de los hallazgos de Ferreira et al. (2012) y de algunos autores que han estudiado los fondos estadounidenses. Vemos que, en promedio, las comisiones por salida de fondos de inversión en Colombia están relacionadas positivamente con el rendimiento debido a que esta condición disuade de la salida y favorece el rendimiento, ya que el gestor puede disponer de más dinero para invertir en mas títulos o activos. Encontramos fuerte evidencia de este resultado en los fondos de *money market*, que representan más de dos tercios de los fondos de nuestra muestra. También observamos que los fondos de *equity* y deuda de mayor edad ofrecen un mayor rendimiento que los de menor de edad, mientras que los fondos de *money market* más jóvenes ofrecían un mayor rendimiento que los fondos más antiguos. Encontramos evidencia que es consistente con investigaciones previas que señala que los fondos cerrados en Colombia están relacionados positivamente con el rendimiento (Coles et al., 2000; Khorana et al., 1999). Encontramos evidencia de que el rendimiento histórico de los fondos de *money market* tiene un efecto positivo en el rendimiento futuro, pero también vemos un efecto poco significativo del rendimiento histórico en el rendimiento futuro para el caso de los demás grupos de fondos según nuestra clasificación.

Nuestros hallazgos también indican que la actividad comercial de los fondos de inversión en Colombia está relacionada negativamente con el rendimiento. Una explicación para este hallazgo, coherente con investigaciones previas (Ferreira et al. 2012), es que la liquidez del mercado financiero colombiano puede redundar en algunas desventajas con respecto a mercados financieros más desarrollados. Los mercados financieros más desarrollados tienen una mayor liquidez que los mercados pequeños, como es el caso de Colombia; así, una menor liquidez redunda en mayores costos de transacciones y, por tanto, un menor rendimiento. Nuestros resultados también son consistentes con la hipótesis del dinero inteligente de Gruber (1996), dado que encontramos evidencia de que el flujo de dinero en fondos de deuda, fondos balanceados y fondos de renta están relacionados positivamente con el rendimiento. No encontramos evidencia de que los fondos gestionados por equipos ofrezcan un rendimiento inferior a los fondos gestionados por una sola persona, tal como se ha mostrado en otros estudios (Ferreira et al., 2012; Massa, Reuter y Zitzewitz, 2010; Chen et al., 2004; Stein, 2002; Aghion y Tirole, 1997). Por el contrario, observamos que los fondos gestionados por un equipo pueden tener un mayor rendimiento o posiblemente el mismo que los fondos gestionados por un solo gestor. Esta evidencia amplía el hallazgo de Bliss, Potter, y Schwarz (2008), que también observan que los fondos gestionados por un equipo tienen el mismo rendimiento que aquellos gestionados por un solo gestor.

Por último, no vemos una diferencia significativa entre los resultados de los determinantes del rendimiento de los fondos de inversión obtenidos a través de nuestro modelo de regresión usando de índices de referencia de Sharpe y el modelo de regresión usando el índice de referencia basado en los prospectos. Por tanto, no encontramos evidencia concluyente que demuestre que las compañías administradoras de fondos en Colombia estén interesadas en manipular intencionalmente los prospectos informativos o los informes técnicos para proporcionar una visión distinta de sus actividades de gestión. No obstante, observamos que el regulador y las compañías administradora de los fondos no recopilan de forma sistemática y publican toda la información necesaria para ofrecer una visión homogénea de las decisiones de inversión en la industria de fondos de inversión en Colombia, lo que deja esta costosa tarea en manos de los inversionistas. Por tanto, nuestros hallazgos respaldan nuestra hipótesis de que los inversionistas en Colombia no cuentan con una información adecuada, fácilmente accesible y precisa para evaluar el rendimiento de los fondos en el mercado colombiano.

Las implicaciones de nuestros resultados son de gran alcance. El sistema de clasificación basado en retornos empleado en esta tesis puede ser usado por los fondos de inversión en mercados emergentes para desglosar los diferentes estilos en mediciones más homogéneas y familiares, según como lo argumentan Brown et al. (1997). Este análisis de estilos y la clasificación empírica de estilos pueden servir como métodos valiosos para ayudar a los inversionistas a alcanzar sus objetivos de manera más eficiente. Nuestro estudio ofrece un microfundamento de las alfas estimadas tras el análisis de estilos de Sharpe (1992). Desde la perspectiva de los investigadores interesados en entender el comportamiento de los fondos de inversión en mercados emergentes, este estudio incorpora un procedimiento atractivo y sistemático que nos permite comprobar si las diferencias de estilo están asociadas a diferencias en el rendimiento. Desde una perspectiva de gestión, este estudio sugiere a los inversionistas que busquen oportunidades de diversificar sus portafolios en mercados emergentes, especialmente en Colombia, directrices que pueden ser de utilidad para entender los problemas planteados por este tipo de inversión, así como mantener la alineación de los intereses sin afectar al rendimiento y la ejecución del contrato. Este análisis también ayudará a los gobiernos y a los reguladores a formular las políticas que controlen estas transacciones dado que el efecto de los incentivos en el rendimiento ajustado al riesgo debería tener implicaciones importantes en las políticas implementadas.

El resto de este documento se organiza como sigue. La sección III ofrece una descripción del marco teórico subyacente en la industria de los fondos de inversión. La sección IV ofrece una descripción de la construcción de la muestra de datos y todas las variables. En la sección V presentamos nuestra metodología empírica y los hallazgos asociados a la clasificación de estilos y la identificación de índices de referencia que determinan el rendimiento ajustado al riesgo como la base para la comparación y la medición del rendimiento. En la sección VI presentamos nuestros hallazgos empíricos con respecto al análisis de panel y sección cruzada de los determinantes del rendimiento de los fondos de inversión en

Colombia. En la sección VII presentamos nuestros hallazgos empíricos asociados a la relación univariada entre retornos antes de comisiones y retornos esperados ajustados al riesgo, y comisiones. En la sección VIII explicamos la relación entre comisiones y rendimiento tal como se analiza en la sección VII y presentamos nuestros hallazgos empíricos acerca de cómo las características de los fondos pueden afectar a la comisión de compensación. En la sección IX presentamos nuestros hallazgos empíricos acerca de la forma en que las características de los fondos pueden determinar el rendimiento de los fondos de inversión en Colombia. En la sección X ofrecemos nuestras conclusiones.

3. THEORETICAL FRAMEWORK

3.1. Style classification and performance

Sharpe (1992) argues that the traditional view of investment allocation assumes that an investment advisor allocates assets among funds on behalf of investors. Each fund holds a different type of security. The investor then is exposed to the key asset classes associated with the investment allocation. This author pointed out that “the asset classes are a function of i) the amounts of the investor’s portfolio invested in the various funds and ii) the exposures of each such fund to the asset classes. The exposures of a fund to the various asset classes are, in turn, a function of i) the amounts that the fund has invested in various securities and ii) the exposures of the securities to the asset classes” (Sharpe, 1992: page 6).

Some authors (e.g., Neus & Walz, 2004; Stracca, 2006) emphasize the relevance of agency theory to understand investor behavior during the investment and divestment process.[11] As noted by Chan et al. (2002), for agency reasons, the results on a fund’s styles highlight the potential importance of assessing performance distortion, given that the behavior of mutual fund managers may be affected by considerations beyond the maximization of portfolio returns or diversification.

One common approach to evaluate performance is the returns-based style analysis, which consists of extracting from the portfolio returns provided by asset managers the maximum information possible about fund performance, strategy,

[11] Agency problems occur when cooperating parties have different goals and divisions of labor (Jensen & Meckling, 1976).

and risk-taking. As Wermers (2011: page 541) states, the goal of this approach involves “the application of the best possible econometric models, based on i) the application of proper benchmarks (types of risks taken by fund managers), ii) the breakdown of systematic versus idiosyncratic risks taken by the managers (selection of proper benchmarks and the detection of dynamic risk-taking strategies by managers), and iii) the statistical distribution of the returns to both systematic and idiosyncratic risks (that is, both can be nonnormally distributed).” This approach has been applied with some success to debt–stock portfolios to infer the types of securities held by a fund manager to explain the investment strategy made by asset managers simply by studying past returns; see, for example, Elton, Gruber, Das and Hlavka (1992); Sharpe (1992); Blake et a (1993); Brown et al. (1997); Fung and Hsieh (2004); and Barras et al. (2010).

In the finance literature, style classification is widely used as the basis for performance measurement and compensation (Sharpe, 1992; Brown and Goetzmann, 1997). This characterization has traditionally been performed according to parameters estimated using linear asset pricing methods to classify mutual funds on the basis of systematic risk characteristics.[12] Numerous studies generally indicated that quantitative methods to aggregate financial assets, such as classification algorithms using a linear models; switching regressions and hierarchical clustering methods; principal component analysis; quadratic programming to determine a fund’s exposure to changes in the return of major asset classes; and cluster analysis and style classification algorithm based on the cross-

[12] See, for example, Jensen (1968), Connor and Korajczyk (1986), Lehmann and Modest (1987), and Grinblatt and Titman (1988, 1989).

sectional time series of past returns have been proven useful for grouping securities and forecasting cross-sectional differences.[13]

Brown and Goetzmann (1977) show evidence that the mutual fund's industry classification has relatively little power to explain differential fund performance. Thus, they employed a procedure that is a potential useful tool and brings advantages over a heuristic classification by allowing decomposing styles into more familiar measures, such as "time-varying factor loadings and risk premiums."

However, the application of a proper style benchmark asset class is extremely important under the returns-based style analysis because the evaluation of investment fund results are very sensitive to the benchmark selected for evaluating funds' ability to outperform a passive strategy (Blake et al., 1993; Brown and Goetzmann, 1997) and needs assumptions associated with strategies developed by managers that generate returns (Warmers, 2011).

Ben Dor and Jagannathan (2002: page 3) point out that an adequate style classification "provides a way of identifying the asset mix style of the fund manager and comparing it with the asset mix style of the performance benchmark." This classification enables an evaluation of how well an active manager performed and whether he provided diversification benefits in a multimanager portfolio. Thus, the most well-documented problem is the choice of inefficient benchmarks, giving rise to a performance evaluation in an ambiguous manner (Wermers 2011).

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13 See, for example, Elton and Gruber (1970), Carleton and McGee (1970), Connor and Korajczyk (1991), Sharpe (1988, 1992), and Brown and Goetzmann (1997).

Chan et al. (2002: page 1417) point out that “taking at face value the evidence on return anomalies, an outside observer might expect to find that investment funds should aggressively pursue certain investment strategies that have been documents to produce superior results in the past.” However, these authors pose an alternative interpretation in which managers prefer choosing portfolios that do not deviate from benchmarks because they might face high personal risk in adopting these styles (see, for example, Lakonishok, Shleifer and Vishny (1997), Chan, Chen and Lakonishok (2002)).

This approach is roughly consistent with the hypothesis that the average mutual fund cannot “beat the market” before costs because such funds constitute a large (and presumably representative) part of the market (Sharpe, 1992: page 24). In this sense, a positive relationship between the performance obtained in investment funds and returns obtained by passive benchmark should exist because of the personal risks that managers might face when adopting a different style. Thus, investment funds as a group should not outperform a passive benchmark because managers choose portfolios that do not deviate markedly from benchmarks.

As Stracca (2006) notes, portfolio managers do not truly have any incentive to increase the overall volatility of their portfolios except for the variance of the tracking error, that is, the departure of their portfolios from the benchmark portfolio (Chen and Pennacchi, 2002). Chen and Pennacchi (2002) show that worsening performance might actually move the portfolio closer to that which minimizes variances in absolute returns.

Numerous studies generally indicate that mutual funds as a group do not outperform passive benchmarks,[14] whereas other studies examine whether performance is persistent.[15] The size and value of the funds explained differences in fund performance, and few authors directly compare more general style factors (Brown and Goetzmann, 1977; Carhart, 1997). Grinblatt and Titman (1989a) and Daniel et al. (1997) use funds' characteristics instead of basing a fund's style on variations in its return to factors.

Li and Tiwari (2009) show that, under a moral hazard, the manager's compensation should include a convex, option-like component whereby the manager is rewarded for outperforming the benchmark but receives no penalty for underperformance. Importantly, the optimal benchmark choice should reflect the manager's investment style. More recently, Garleanu, Panageas and Yu (2017) study a general equilibrium model through which portfolio managers exhibit stock-picking ability. They show that a relative performance evaluation with respect to a style index is optimal. Both studies offer a microfoundation of the alphas estimated following the style analysis of Sharpe (1992), which we use in this thesis.

The other commonly used approach to evaluating performance is the use of a portfolio-based style analysis, which consists of examining the portfolio composition of the funds and comparing the characteristics or attributes of the securities in which the manager has invested with the characteristics of the securities that make up the performance benchmark. Grinblatt and Titman (1989a) are the

[14] See, for example, Jensen (1968), Ippolito (1989), Sharpe (1992), Elton et al. (1993), and Malkiel (1995), Chen et al. (2002).
[15] See, for example, Grinblatt and Titman (1992); Hendricks, Patel and Zeckhauser (1993); Brown and Goetzmann (1995); Elton, Gruber, and Blake (1996).

first to use the portfolio-based approach (or portfolio-holding). This study breaks new ground by examining performance “using holdings applied to changes in the closing price quotations of stocks to compute the return of an asset manager” (Werners, 2011; page 551). Others academic researchers build on Grinblatt and Titman (1989a) with some success. They develop additional measures of portfolio performance to allow the holdings or portfolio weights to “play a more central role” in the formation of the benchmark (Wermers, 2011). See, for example, Grinblatt and Titman (1993); Ferson and Schadt (1996); Kothari and Warner (2001); and Wermers (2010). However, the main disadvantage of this approach is that the portfolio composition—or holding data—is not always available, making application difficult.

The absence of a detailed style classification might enable investment advisors or fund managers to combine investment securities indistinctively, which results in a lack of style specialization among investment companies and the impossibility of accurately evaluating fund and management performance. This situation offers managers great latitude in the type of securities that they can hold, the timing of purchases and sales, the level of fund diversification, the industry concentration of the portfolios, and a host of other factors that determine the return on their clients’ investments. Thus, not surprisingly, widely divergent behaviors among funds allegedly pursing the same investment objective is found in the Colombian mutual fund industry. Arguably, this lack of transparency jeopardizes the alignment between the interests of investment companies and their clients (Brown et al., 1997; C. Chan et al., 2002). Ultimately, the absence of a clear style classification system makes performance forecasting and attribution extremely challenging. Therefore, and to understand whether investors in Colombia have the right information to evaluate fund performance, we develop the following three goals.

Our first goal is to use a style classification—described in greater detail in chapters 4 and 5—to the extent that it successfully explains out-of-sample fund performance in Colombia to determine a natural grouping of funds that have some predictive power in explaining fund returns (Brown et al., 1997). The objective of using this style analysis is to select the style or set of asset class exposures that minimizes the variance ("tracking variance") in the fund's "tracking error" (Sharpe, 1992).

Our second goal is to investigate how well the estimated funds styles might explain cross-sectional variations in out-sample fund returns.

Our third goal is to provide an overview of the strategies that differentiate advisors by employing the estimated funds' styles classification.

3.2. Compensation fees and performance

Under advisory contracts, portfolio management might be viewed as one of the primary services of suppliers to investors (Baumol et al., 1990; Deli, 2002). The activities that portfolio management might include, among others, are conducting research and making fund investment decisions on behalf of investors.

In the majority of the cases, advisors receive compensation fees in return for providing those services. The advisory fee is specified as a percentage of the fund's total assets (e.g., Deli (2002)). In addition, some investment funds compensate their investment advisors using incentive fees based on fund investment performance. The structure of the advisory fees in Colombia are largely unconstrained by regulations. We suspect that contracts based solely on a percent of assets comprise an overwhelming majority of advisory contracts in Colombia and no prespecified benchmark exists to determine the incentive fee. Asymmetric performance fee contracts are those that compensate advisors for portfolio gains but do not penalize advisors for portfolio losses (Deli, 2002). In Colombia, no prohibition exists on asymmetric incentive fees and contracts among investors, and the advisory company is not subject to restrictions.

The uncertainties regarding what an investor may face under advisory contracts—not only before making any investing but also during the entire investment horizon—generates moral hazard problems.[16] We observe this situation in the investment fund industry in Colombia: if investors systematically do not have all of the information to evaluate investment fund performance, they do not perfectly observe the actions of the advisory company;[17] that is, advisory companies and regulators provide no systematical information that is not available or verifiable by the investors.

One governance mechanism to reduce the moral hazard is to monitor agents' actions and reward them when they act in accordance with investors' interests. However, when the agent has high autonomy, independence, and highly specialized knowledge, monitoring becomes very difficult and expensive;

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[16] Moral hazard is the condition under which the principal cannot be sure if the agent has put forth maximal effort or if it has engaged in self-serving decisions (Eisenhardt, 1989).

[17] The literature distinguishes two types of moral hazards: hidden action and hidden information. The former refers to cases in which the action performed by the agent is not a verifiable variable. The latter refers to cases in which the action performed by the agent is a verifiable variable, but the agent has private information that ultimately permits the determination of what would be the appropriate action. (Tirole, 1988; Arevalo and Ojeda, 2004)

therefore, principals rely on incentives or compensation tied to verifiable variables to reward agents for appropriate outcomes (Harris and Raviv, 1979; Holmstrom, 1979; Grossman and Hart, 1983; Tosi & Gomez-Mejia, 1989; Zajac and Westhphal, 1994).

Linking advisor payoffs to advisor actions mitigates the agency conflict between investors and advisors when advisor actions are observable (Deli, 2002). However, linking advisor payoffs to advisor actions becomes problematic when managerial actions are not observable or only observable with some degree of noise (see, for example, Holmstrom, 1979; Shavell, 1979; Grossman and Hart, 1983; Gompers and Lerner, 1996; Deli, 2002).

Agency theory claims that when monitoring advisor actions is difficult, tying advisor payoffs to performance becomes optimal (see, for example, Gompers and Lerner, 1996).[18] In such contracts, the expectation is that advisory compensation is more related to their performance, which could increase the advisory effort and lead to better performance.

Coles, Suay, and Woodbury (2000: page 1386) suggested that "compensation policies should give the advisor incentives to take actions that maximize the wealth of the investors. Such actions could include effort allocated toward legally minimizing taxes, fundamental or technical analysis to improve returns, minimizing transaction costs, and configuring portfolio risk to match the risk profile desired by fund shareholders."

[18] Gompers and Lerner (1996) find evidence consistent with the argument that investors can alleviate some agency problems through performance contracts for the agent in the hedge fund industry (Deli, 2002).

Deli (2002) points out that the shape of compensation fee advisory contracts varies in the degree of concavity. A potential cost is associated with less concave payoffs, as Grinblatt and Titman (1989a) state, because “the less concave the payoffs, the greater are their incentives to increase fund risk to maximize expected fees” and, hence, “greater expected fees result in lower expected wealth for investors” (Deli, 2002: page 114). Deli (2002) argues that advisors have stronger incentives when contracts are observed to be less concave because they are incentivized to assume more portfolio risk than more concave contracts. That compensation shape, as Deli (2002) states, is likely to be more valuable when the fund type implies higher volatilities. This argument suggests that more volatile funds should be structured to have less concave advisory contracts than less volatile funds. Thus, equity funds that should be more volatile than debt or money market funds (see, for example, Khorana, 1996) ought to be structured with less concave advisory contracts because doing so gives advisors stronger incentives to assume more portfolio risk than more concave contracts.

The structure of advisory fees in Colombia, as described in greater detail in chapter 3, is primarily not concave, and performance fee contracts are small. Considering these arguments, we should expect that more volatile funds (or equity funds) are more likely to be structured using explicit performance-based incentives than less volatile funds (or debt or money market funds) assume more portfolio risk.

Tufano and Sevick (1997) note that advisory contracts are the product of advisory firms themselves. If compensation rates are used as a signaling mechanism for advisor marginal products, and the difficulty of monitoring advisor actions is captured by the volatility of fund returns (Khorana, 1996; Deli, 2002), then in environments requiring greater advisor marginal products, higher compensation rates are observed as a means of aligning their interests (Deli, 2002). Additionally, as Fama and Jensen (1983a, 1983b) point out, open-end mutual funds offer "a special form of diffuse control" because investors may affect the permanence of the fund by redeeming their shares. Deli (2002: page 113) argues that the "constant threat of withdrawal" of fund assets serves as a disciplining mechanism for open-end fund advisors. Disciplining is not present for closed-end fund advisors. The absence of this discipline may result in the "use of contractual alternatives to better align advisor and investor interests." If the previous arguments are correct, higher compensation rates are more likely observed in equity funds than in bonds and money market funds and in closed-end than open-end funds as a means of aligning their interests.

In a well-functioning market and with the absence of market friction, the theory predicts that fees should be positively correlated with the expected risk-adjusted returns before expenses and, in equilibrium, should have zero expected risk-adjusted returns after expenses (Berk and Green, 2004; Gil-Bazo et al., 2009). Thus, if investors know funds' alphas, then equilibrium requires zero expected returns. If investors do not know funds' alphas, the equilibrium condition of Berk and Green (2004) is achieved through adjustments in i) fees or ii) money flows. Through the fee adjustment, investment funds with higher expected risk-adjusted returns before expenses should have a higher fund fee. Conversely, underperforming funds should have lower fund fees (Gil-Bazo et al., 2009).

Through the flow of money adjustment, if returns are decreasing by fund size, funds with higher expected risk-adjusted returns should attract higher money flows to reduce those funds' expected performance to normalize expected adjusted returns after expenses for all funds (Berk and Green, 2004). However, Christoffersen and Musto (2002) and Gil-Bazo and Ruiz-Verdú (2009) find a negative relationship between fees and before-fee performance.

3.3. Fund characteristics and compensation fees

As Christoffersen and Musto (2002) and Gil-Bazo and Ruiz-Verdú (2009) posit, the compensation of investment funds might be explained in terms of the "elasticity of demand" for funds' securities. Those authors state that funds with less elastic demand or low performance sensitivity charge higher fees. Moreover, these authors state that overperformance funds compete for the money of "sophisticated" investors; thus, this competition reduces fees and triggers underperformance funds to leave that segment of the market. Hence, underperformance funds should target "unsophisticated" investors to whom they are able to charge higher fees. Thus, by targeting this investor, funds with bad performance will have higher operating costs.

As Gil-Bazo et al. (2009) posit, fund performance might be positively related to funds' total expenses because higher expenses might be synonymous with larger investments in research tools and higher salaries for "more talented managers." However, some arguments exist for a negative relationship between funds' fees and performance. If fees reflect the costs of operating a fund, then having low costs—from the competition among them for the resources of "performance-sensitive investors"—should be associated with better performance and, hence, result in a negative relationship between fees and performance (Gil-Bazo et al., 2009). As stated, funds' operating costs could be lowered in different ways. Economies of scale might be one such way because operating costs should decline as funds grow. Thus, better performance should be associated with larger size if performance is persistent with past results, suggesting lower operating costs. Learning economies might also reduce the operating costs for older funds if they are able to translate this experience in lower fees to investors. Talented managers may be associated with lower operating costs because talented managers might make better investment decisions and have more efficient fund operations, which would reflect lower costs. Moreover, as Christoffersen and Musto (2002) posit, money market investment funds with persistent bad performance will not be attractive for current investors (less performance-sensitive) and, thus, will abandon those funds following a bad performance. Therefore, these underperforming funds will charge higher fees because these conditions will not cause significant money to flow out of the fund (Christoffersen and Musto, 2002; Gil-Bazo et al. 2009). In this regard, Gil-Bazo (2009) also state that funds with bad performance traditionally charge higher fees because they believe that they cannot compete with overperformance funds in a market with sophisticated investors. Thus, they will focus on investors that are not sensitive to performance.

The literature on mutual fee determinants, such as Sensoy (2009); Gil-Bazo et al. (2009); Huang, Wei, and Yan (2007); Barber, Odean, and Zheng (2005); Nanda, Wang, and Zheng (2005); Christoffersen and Musto (2002); Jain and Wu (2001); Sirri and Tufano (1998); Chevalier and Ellison (1997); Gruber (1996); and Ippolito (1992), have shown that flows of money are positively related to performance after expenses. Further, the flow-to-performance sensitivity declines (becomes less convex) when a fund's compensation fee decreases (Gil-Bazo et al., 2009; Huang, Wei, and Yan, 2007). As Christoffersen and Musto (2002) posit, funds with experienced high money outflows have the least performance-sensitivity investors; that is, a positive relationship exists between flow-to-performance and performance sensitivity. Finally, these prior studies also show that flows of money depend on fund size, age, TER, lagged flows, volatility, lagged expected performance return, and performance sensitivity.

3.4. Fund characteristics and performance

Fund characteristics, such as size, age, front-end and back-end loads, flows, and management structures, have a variety of effects on a mutual fund's performance (e.g., Ferreira et al., 2012).

Ferreira et al. (2012: page 18) argues that when funds are small, they "can concentrate on a few investment positions, however, when they become large, managers must continue to find good investment opportunities, and the effect of managerial skill becomes diluted, implying diseconomies of scale." Moreover, these authors argue that "larger mutual fund managers trade larger volumes of stock, attracting the attention of other market participants and therefore suffering higher price impact costs." Chen et al. (2004) call this effect the liquidity constraints hypothesis. Edelen, Evans, and Kadlec (2007) and Yan (2008) point out that trading costs and liquidity are the primary sources of diseconomies of scale for U.S. funds. Thus, the scale ability of investment funds is a determining factor of performance persistence (Gruber, 1996; Berk and Green, 2004).

Grinblatt and Titman (1989b, 1994) find mixed evidence on the relationship between fund returns and fund size. Chen et al. (2004) find that fund size erodes performance because of liquidity and organizational diseconomies. Pollet and Wilson (2008) find that fund size erodes performance because of the inability to scale an investment strategy related to liquidity constraints as the fund grows. Dahlquist et al. (2000) find that larger equity funds in Sweden tend to perform more poorly than smaller equity funds. More recently, Ferreira et al. (2012) find that fund size is negatively related to fund performance for U.S. funds. He also finds that this result is different for mutual funds outside the United States because of the difference in size between U.S. and non-U.S. funds. If these arguments are correct, fund size is expected to be negatively related to fund performance because economies of scale should be exhausted after a fund approaches a certain size in fund assets.

Regarding fund family size, economies of scale and scope might generate a positive effect at the fund family level that leads to higher returns because, as stated by Ferreira et al. (2002: page 19), "expenses like research and administrative expenses can be shared among funds, and larger fund families can use the same economic data and experts to interpret data across many funds." Chen et al. (2004) find that fund family size has a positive and statistically significant effect on performance because large fund families capture economies of scale from trading commissions and lending fees. Khorana and Servaes (1999) find that large families benefit from economies of scale and scope because, if they have more experience opening funds in the past, they are more likely to have opened new funds and, thus, have lower costs than smaller companies related to generating a new fund. Ferreira et al. (2012) find that fund family size has a positive and statistically significant effect on the performance of mutual funds. Under these arguments, the expectation is that funds that perform better are more likely to be managed by a larger company because family size has a positive effect on fund performance.

Regarding fund age, Ferreira et al. (2012) states that the effect of age on performance can “run” in both directions because younger mutual funds will be more agile and committed to achieve better performance to survive. Additionally, younger mutual funds typically face higher costs and suffer from a lack of experience during the startup period. Chen et al. (2004) and Ferreira et al. (2012) find no relationship between the age and performance of U.S. mutual funds. However, for mutual funds outside the United States, Ferreira et al. (2012) finds that newer funds seem to perform better than older funds. Considering that funds in Colombia should be much smaller than those in the United States, we should suspect that a negative overall relationship exists between fund age and fund performance. However, younger funds might be able to perform better than older funds because newer funds will be more agile and committed to achieve better performance.

Funds commonly charge a load when investors purchase (front load) or sell (back-load) shares (Ferreira et al., 2012). These loads are paid at the time of purchasing or redeeming a fund’s securities. Back-end loads discourage redemptions. As Ferreira et al. (2012) state, by making redemptions expensive, a mutual fund dissuades investors from redeeming securities.[19] In this case, they are able to find better portfolio opportunities. Chen et al. (2004) and Ferreira et al. (2012) find no relationship between performance and loads, but Carhart (1997) and Pollet and Wilson (2008) find a negative relation. Considering these arguments, a positive relationship between performance and back-end loads and no clear relationship with front-end loads are expected.

Regarding fund flows, Gruber (1996) finds that the flow of new money into and out of mutual funds follows predictors of future performance. Some authors show that funds experiencing net inflows perform better than funds experiencing outflows (see, for example, Gruber, 1996; Zheng, 1999). Investors can detect skilled managers and direct their money to them, which is the smart money hypothesis by Gruber (1996). Therefore, fund flows should have a positive correlation with future returns. However, Sapp and Tiwari (2004) argue that the smart money effect is explained by momentum. Ferreira et al. (2012) find no evidence of a relationship between flows and performance in the sample of U.S. funds; however, they find evidence that non-U.S. funds that receive more new money perform better than those that receive less new money, indicating a smart money effect. According to Ferreira et al. (2012), the evidence supports the idea that investors are able to detect skilled fund managers outside the United States. This result is consistent with Sapp and Tiwari (2004). If these arguments are correct, a positive correlation should exist between fund flows and performance.

[19] See, for example, Chordia (1996) who show empirically that evidence exists that loads dissuade redemptions in open-ended funds.

Regarding managers' structure and performance, Chen et al. (2004) find that funds managed by one manager are better at tasks involving processing soft information than are funds managed by many managers. This concept is consistent with Stein (2002) because funds managed by one manager are more likely to invest in and pick better local stocks than funds managed by many managers. According to Chen et al. (2004), this concept is explained as follows: when a fund is managed by more than one manager, more competition exists among the managers, who end up making greater efforts to convince others to implement their ideas than they would if they controlled their own funds (Aghion and Tirole, 1997; Stein, 2002). Thus, evidence exists from U.S. mutual funds that funds managed by teams (or more than one manager) show significantly worse performance than funds managed by one manager (Chen et al., 2004; Massa, Reuter, and Zitzewitz, 2010; Ferreira et al., 2012). However, evidence also shows that funds managed by a team perform no differently than a fund managed by a single manager (Bliss, Potter, and Schwarz, 2008). Considering that approximately 99% of the investment funds in Colombia are managed by one manager and a small fraction of the funds are listed as managed by a team, we will not be able to provide clear evidence of this relationship among Colombian investment funds.

Golec (1996) examines the effect of a relationship between a manager's education and tenure on performance in U.S. mutual funds. He suggests that performance may be positively related to tenure because a long tenure may imply greater job security and, hence, less short-term behavior by the manager. Considering that tenure measures managers' survivorship at the job, a long tenure may imply that the management company finds the manager's ability and performance satisfactory but may also indicate that the manager has fewer better opportunities because of specialized skills or an unspectacular performance record. Moreover, Golec (1996) finds that years of education, particularly holding an MBA, has a positive relationship to performance because a specialized business education should lead to better performance. Chevalier and Ellison (1999: page 876) suggest that mutual fund managers who attended more selective undergraduate institutions have higher performance than mutual fund managers who attended less selective undergraduate institutions because a better education might reflect differences in "stock-picking" ability or direct benefits. Moreover, they find that fund performance also increases slightly with tenure. Gil-Bazo et al. (2009: page 2166) suggest that "higher managerial skill may be associated with both better investment decisions and more efficient management of fund operations, which would translate into lower operating costs." If these arguments are correct, a positive relationship among performance and higher education and tenure, respectively, is expected.

4. DATA AND MAIN VARIABLES

4.1. Investment fund industry in Colombia

The growth of the mutual fund industry started in the United States (Ferreira et al., 2012). Given that the mutual fund industry plays an important role in the development of financial markets, the growth of the investment funds has spread broadly to other countries, including emerging markets (Khorana, Servaes, and Tufano, 2005). For instance, Ferreira et al. (2012) point out that investment fund assets outside the United States grew from 38% in 1997 to 54% of total assets in 2007.

This scenario is not the exception in the Colombian context. Public interest in the Colombian investment fund industry has grown rapidly. At the end of 2015, the investment fund industry in Colombia managed financial assets exceeding COP 56 billion (approximately USD 17.5 billion[20]), whereas this amount was COP 29.3 billion[21] (approximately USD 9.2 billion) in 1999 (see Table I), representing growth of 92% from 2009 to 2015. Additionally, the number of investment funds has grown dramatically, from 198 funds in 2009 to 403 funds at the end of 2015.

In Colombia, the definition of investment funds (or "*carteras colectivas*" in Spanish) is similar to what is known in the United States or Europe as mutual funds. They are investment vehicles managed by advisory companies in which investors deposit their money for investments in a diversified portfolio of assets, such as stocks, bonds, and money market instruments. Once the investment fund

[20] Converted into USD at the COP exchange rate on December 31, 2015 USD 1 equals COP 3,191.68).
[21] Information extracted and analyzed from the Superintendence of Finance in Colombia.

is in operation, its resources are managed collectively to obtain economic results, also collectively.[22]

The evolution of investment funds in Colombia is divided in two stages marked by the entry into force of Decree 2175 of 2007 issued by the Ministry of Finance, which ruled the administration and management of investment funds (or "*carteras colectivas*"). Before the entry into force of Decree 2175 of 2007, investment funds in Colombia were classified into four types of funds: security funds, investment funds, ordinary common funds, and especial common funds. During this stage, investment funds in Colombia grew significantly; however, some deficiencies existed in how the system worked. For instance, each type of fund had an independent applicable regulation, was administered by different types of advisory companies, and was monitored by different government superintendences. The existing regulation at this stage did not ensure that investors received clear and sufficient information about the risks of products in which they were already investing their resources; thus, the regulation was not appropriated and adjusted to the reality and needs of the Colombian market (Ramirez 2012).

With the entry into force of this regulatory framework (Decree 2175 of 2007), the aim was to solve part of the problems identified and to develop an agile and efficient investment fund industry, in which investors would come with more confidence and with full guarantee of their rights to the financial market

[22] Section 3 of Decree 2555 of 2010 issues by the Superintendence of Finance in Colombia.

through said vehicles. This regulation gathered experiences from more developed countries in the investment fund industry, such as the United States and some European countries (Ramirez, 2012).

Under this regulation, investment funds in Colombia were renamed locally as "*carteras colectivas*" because the intent was for any investment fund scheme to have a unique identity and not be confused with any of the four types of investment funds that previously existed in the Colombian regulation (Ramirez 2012).

Decree 2175 of 2007, which was merged into section 3 of Decree 2555 of 2010 and then replaced by Decree 1242 of 2013, defined investment funds (or "*carteras colectivas*") as any mechanism or vehicle for collecting or managing sums of money or other assets, integrated with the contribution of a plural number of persons determinable once the collective portfolio goes into operation. The resources are managed collectively to obtain economic results, also collectively.

Decree 2175 of 2007, Decree 2555 of 2010, and Decree 1242 of 2013 state that investment funds can only be administered by three types of entities: company stock brokers ("*sociedades comisionistas de bolsa*" in Spanish), investment management companies ("*sociedades administradores de inversiones*" in Spanish), and trust companies ("*sociedades fiduciarias*" in Spanish).

At the end of 2015, more that 71% of the investment fund industry was managed and controlled by trust companies ("*fiduciarias*"), whereas the rest was managed by company stock brokers ("*comisionistas*") and investment management companies ("*sociedades administradores de inversiones*"). Although trust companies reduced their market share from 2009 to 2015 because of the competence of stock brokers (see Table 1), trust companies remain the most representative type of advisory company in the Colombian context because they still manage financial assets exceeding COP 40 billion (approximately USD 12.53 billion[23]).

Table 1: Investment Fund Industry in Colombia

Investment Funds managed by Trust Companies ("Fiduciarias"), Stock Brokers ("Comisionistas") and Investment Management ("Administradores de Inversiones")	Total Assets under management - Investment Funds (COP Million)						
	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Investment Funds managed by Trust Companies ("Fiduciarias")							
Investment Funds	24,098,383	26,558,336	32,203,481	37,203,980	40,447,413	42,221,180	40,209,729
Participation of total market	82.2%	76.3%	75.5%	74.0%	74.7%	71.0%	71.4%
Investment Funds managed by Stock Brokers ("Comisionistas") and Investment Management ("Administradores de Inversiones")							
Investment Funds	5,231,877	8,266,283	10,446,488	13,076,024	13,697,084	17,263,151	16,092,429
Participation of total market	17.8%	23.7%	24.5%	26.0%	25.3%	29.0%	28.6%
Total Investment Funds	**29,330,260**	**34,824,619**	**42,649,969**	**50,280,004**	**54,144,497**	**59,484,331**	**56,302,158**

Source: Superintendence of Finance (Colombia´s SEC)

This table shows the total asset under management by the investment funds industry in Colombia for the period 2009 to 2015. The total asset under management are in million COP and are classified by funds managed by Trust Companies (*"Fiduciarias"*) and Stock Brokers on December 31 of each year. This table also shows the growth of the mutual fund industry in Colombia. At the end of 2015 the investment fund industry in Colombia managed financial assets exceeding COP$56 billion, whereas in the year 1999 the investment fund industry was of COP$29.3 billion. This represents that the public interest in the Colombian investment fund industry has grown rapidly: 92% from 2009 to 2015. At the end of 2015 more that 71% of the investment funds industry are managed and controlled by Trust Companies, whereas the rest is managed by Stock Brokers. Although trust companies have been reducing their market share compared 2009 to 2015, because of the competition with stock brokers, trust companies remain the most representative advisory companies in the Colombian context; since they still managing financial assets exceeding COP$40 billion. For the purpose of our study, we focus only on investment fund managed by trust companies (*"Fiduciarias"*) from 2009 to the end of 2015. By focusing on trust companies, we cover a large part of the investment fund industry because we are considering during the sample period about 71% to 82% of the total asset value under management.

This new regulatory framework classified investment funds into three types: open-end funds, staggered funds, and closed-end funds. Among the open-end funds, the investment company is obliged to redeem the securities, buying and selling them in the market to provide liquidity to investors. For closed-end funds, the investment company does not have this obligation; therefore, if investors want to cash in their fund investments before the term of the fund, then they

[23] Converted into USD at the COP exchange rate on December 31, 2015 ($USD 1 equals COP 3,191.68).

should sell the securities in the secondary market. The staggered fund is a type of open-end fund in which the investment company might redeem the securities at any time but cannot redeem until the fulfilment of a certain period as established in the agreement.

In addition, this new regulatory framework also introduced the classification of the style of investment funds into two main groups: regular or general funds and special funds. In regular or general funds, the investment company buys and sells securities in the market without specifying whether the funds are equity, money market, debt, or mixed. Special investment funds are only divided into the following types of investments, which depend on the characteristics of the assets that comprise the portfolio and the level of risk of the funds: monetary market, real estate, speculative, and stock market.[24]

In addition to establishing these categories, Decrees 2175 of 2007, 2555 of 2010, and 1242 of 2013 also stipulate that each advisory company must define its investment policy in a clear and prior manner in both the prospectus and a technical report that should be published on a monthly basis by the company advisor on its web page. This investment policy must include certain aspects that are important for investors, among which the following should be highlighted: the objective of the portfolio, the assets considered acceptable for investment, the risk profile of the portfolio, the fund's return, and the advisory fee, among others. However, no regulation is in force that stipulates reporting the portfolio holdings, the passive benchmark, and its strategy. Also important to mention is that the

[24] Decree 2175 of 2007 and Decree 2555 of 2010 issued by the Colombian Government.

regulator only obliges the company advisors to keep the technical reports for a maximum of six months on their respective web pages. However, in the praxis, some of the advisory companies keep this information for the most recent past two years.

In addition to the aspects that have already been noted and considering that Colombian investment funds are surveilled by the “Superintendencia Financiera” (Colombia’s SEC), on a monthly basis, Colombia’s SEC publicly reports the daily fund returns, total daily assets under management, number of investors, and net flows.

Thus, any information that investors wants to obtain and assess relative to their investments, in addition to the information publicly available through Colombia’s SEC, needs to be obtained from the technical reports issued by the advisory companies.

At this stage, although the investment fund industry in Colombia has had a strong impulse for development and expansion, partly favored by the current national regulation that was partly inspired by the United States and some European countries, ample room still exists to improve before converging to the standards of more developed markets. The experience and the market itself have shown that more stringent requirements for the disclosure of clear and sufficient information for investors is a necessary improvement. The public information reported by Colombia’s SEC and the information reported by the advisory companies in prospectuses and technical reports are inadequate, difficult to collect, and outdated, which does not allow investors to evaluate the performance of their investments. The current style classification does not allow for an explanation of the differences in future returns. Benchmarks are not available, and the regulator does not publicly report information on investment fund fees or specific regulations on portfolio holdings or manager compensation.

4.2. Sample description

This study examines the relationship among fund performance, fund attributes, and investment fund fees in the Colombian market. We focus only on investment funds managed by trust companies ("*fiduciarias"*) from 2009 to the end of 2015 because this is the only available information reported by the regulator in a consistent manner for our study. In addition, by focusing on trust companies ("*fiduciarias"*), we cover a large part of the investment fund industry because we are considering approximately 71% to 82% of the total asset value under management during the sample period (see Table 1).

The choice of period is explained because before 2009 and during its first semester, the funds were not broadly categorized by the Colombian SEC ("*Superintendencia Financiera"* in Spanish) according to the types and styles defined by Decree 2175 of 2007 and the aforementioned described. The investment funds used to be categorized according to the types of funds that existed before the new regulation; thus, investment fund returns and attributes before 2009 were not consistent.

We collected data from three sources: i) the Colombian Financial Supervising Authority (Colombia's SEC), ii) monthly or annual technical reports of investment funds prepared by advisory companies, and iii) the legal prospectus of all funds.

From the public information reported by Colombia's SEC, we managed to gather electronically daily fund returns, total daily assets under management, number of investors for all funds within the sample period, net flows, fund name and code, name of the advisory company and code, whether the fund is open- or closed-end, and the style classification by the regulator as in Decree 2175 of 2007.

From the monthly or annual technical reports of each investment fund obtained from either the trust company's web page or the advisory company directly, we managed to hand-collect the fund characteristics or attributes corresponding to approximately 90% of the total sample of investment funds. Therefore, we had to extract the fund characteristics or attributes from more than 300 technical reports during the sample period. The hand-collected information from these data source includes commission fees; TER; exit and entry load fees; minimum investment requirements; characteristics of investment managers, such as manager name, seniority or years of experience, and level of education; and fund composition by type of income, type of asset, economic sector, and country of investment. A sample of a fund's technical report issued by one of the company advisories is included in Appendix 1.

From each investment fund's legal prospectus downloaded from the trust company's web page, we obtained the investment policies for all of the funds. Based on this information, we managed to classify whether the funds primarily invest in equity, the money market, debt, or real estate. This manual classification gives us additional information about the style of the funds, given the absence of a more detail style classification provided by the regulator. From this source, we also collect commission fees, exit and entry load fees, minimum investment requirements, and whether the fund is open- or closed-end. All of this information helped us complement and validate the information collected from the technical reports.

Because the data collected from the monthly or annual reports and legal prospectuses were separately collected from the electronic information gathered by the Colombian SEC, we combine the electronic information with the hand-collected data to match the fund characteristics/attributes with performance variable for all individual investment funds. The daily returns obtained were used to calculate monthly returns. We take observations only if the fund existed in the Colombian SEC database to ensure that the hand-collected information on compensation and the relevant variables is complete.

The initial sample was comprised of 275 investment funds between the second semester of 2009 and the end of 2015. Because our sample contains all of the funds that existed during this period, that is, closed and merged funds, the results should not be affected by a survivorship bias. We excluded funds with a primary strategy of foreign investments and that had less than twelve monthly observations because they lacked the observations to estimate an asset class factor model. Thus, the final sample consists of 183 investment funds between the second semester of 2009 and the end of 2015. The unit of analysis is the contract governing the relationship between the investor and the investment company.

Figure 1: Histogram – Number of funds that have existed during the sample period from June 2009 through 2015.

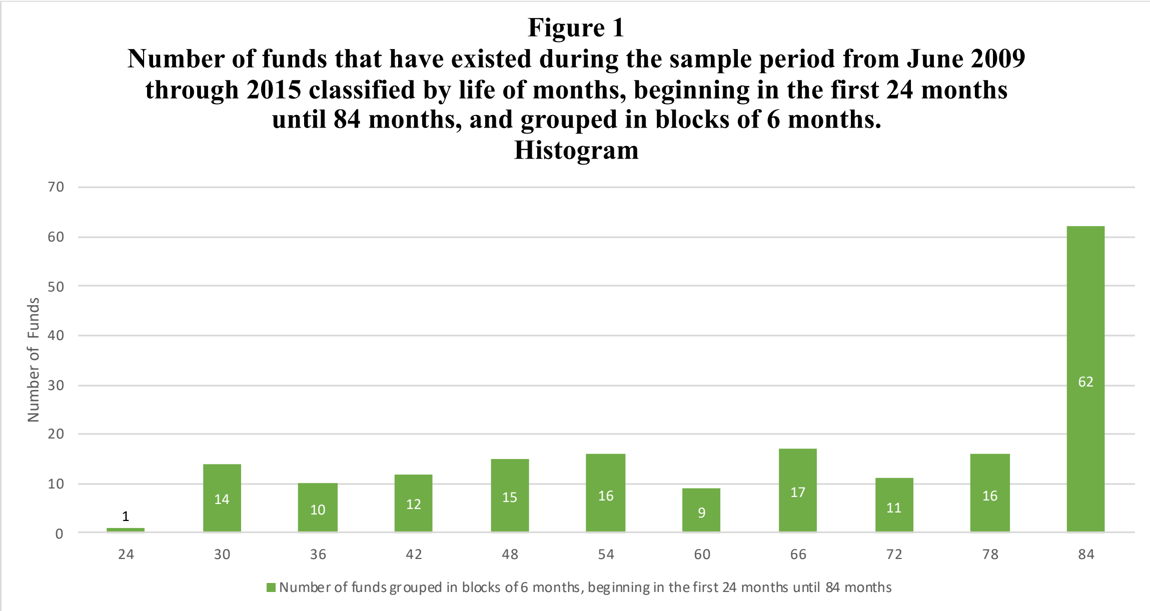


Figure 1 shows the number of funds that existed during the sample period from June 2009 through 2015. In Figure 1, we observe the life in months of all funds classified from the first 24 months to 84 months of the sample period, grouped in blocks of six months. Figure 1 enforces the notion that our sample is free of survivorship bias because we are literately considering all investment funds that have existed during our sample period. In addition, Table 2 shows the number of funds considered in our sample on a year-by-year basis. The number of investment funds has grown dramatically in the sample period, from 101 in 2009 to 160 at the end of 2015.

Table 2: Number of funds during the sample period from June 2009 through December 2015

	year						
	2009	2010	2011	2012	2013	2014	2015
Number Funds	101	129	156	164	168	165	160

This table shows the number of funds managed by trust companies ("*Fiduciarias*") that we have considered in our sample on a year-by-year basis. The number of investment funds has grown dramatically in the sample period from 101 in 2009 to 160 funds at the end of 2015, even though the investment funds were stable over the last four years.

In the first style classification, we consider the investment funds classified by Colombia's SEC. In total, we found in the data source provided by the Government: one equity fund, 166 general funds, six money market funds, and 10 real estate funds. However, given the absence of a more detail style classification from the regulator, we went through the legal prospectuses and technical reports of every fund to understand in greater detail their investment policy and to be able to classify the investment funds based on the basic description encountered by reading the information. Some of the investment funds administered by trust companies are rated by an international rating agency, such as Fitch Ratings and Standard & Poor's, among others, as a best practice. Thus, we support our style classification using the information obtained and from the rating agencies.

The criteria we employed to classify the investment funds were: i) if the legal prospectuses and technical reports stipulate that the investment policies call for investments in assets in the Colombian stock exchange, we classified those funds as equity; ii) if the rating agency classifies the investment fund as a debt fund, we use that classification for those investment funds; iii) if the legal prospectuses and technical reports estipulate that the main strategies call for investments in securities, such as time deposits or fixed rates (DTF or IBR), we classified those funds as money market; iv) if the legal prospectuses and technical reports estipulate that the strategies call for investments in both securities such as time deposits, T-bills, and assets on the Colombian stock exchange, we classified those funds as balanced; v) if the funds classified by the Colombian SEC invest in real estate, we keep the same classification. Considering these criteria, we found 22 equity funds, 120 debt funds, 17 money market funds, 13 balanced funds, and 11 real estate funds. In Table 3, we present a crosstabulation of all funds classified according to Colombia's SEC and the prospectuses and technical reports.

Table 3: Cross-tabulation of all funds by asset-class according to prospectuses and technical reports, and Colombia´s SEC.

Prospectus and Technical Reports asset-class classification	Colombia´s SEC asset-class classification					
	Equity	General	Money_Market	Real_Estate	Speculative	Total
Balanced		13				13
Debt		120				120
Equity	1	21				22
Money_Market		11	6			17
Real_Estate		1		10		11
Total	**1**	**166**	**6**	**10**	**0**	**183**

Source: Superintendency of Finance and Legal Prospectus, Technical reports

This tables reports the cross-tabulation of investment fund under the categories identified in the data obtained by the Superintendence of Finance in Colombia (Colombia´s SEC) and legal prospectus and technical reports of investment funds. We consider in a first style classification, the investment funds classified by the Colombia´s SEC. However, due to the absence of a more detail style classification made by the regulator, we went through the legal prospectus and technical reports of every single fund, in order to understand with more detail their investment strategy and be able to classify the investment funds based on a basic description we encountered by reading said information. The criteria we employed to classify the investment funds under the legal prospectus and technical reports, were: i) if the legal prospectus and technical reports estipulate that the main strategy are investments in asset in the Colombian stock exchange, we classified those funds as equity; ii) if the rating agency employed by the company advisory to rate the investment fund classify the investment fund as debt, we use that classification for those investment funds; iii) if the legal prospectus and technical reports estipulate that the main strategy are investments in securities, like time deposits or fixed rates (DTF or IBR), we classified those funds as money market; iv) if the legal prospectus and technical reports estipulate that the strategy are investments both in securities, like time deposits, T-bills, and in asset in the Colombian stock exchange, we classified those funds as balanced; v) if the funds classified by the Colombia´s SEC are real estate, we keep the same classification.

Under Colombia's SEC classification, more than 91% of the sample in terms of number of funds are classified as "general." The rest are real estate funds (6%) and money market funds (4%). This literal classification is very general for making any conclusions about investment funds in Colombia. Using the prospectuses and technical reports to classify the investment funds, we encounter more diverse investment funds. Under this classification, debt funds represent more than 66% of the sample in terms of number of funds. Money market funds under this classification represent approximately 9% of the funds, equity funds represent 12%, balanced funds represent 7%, and real estate funds represent 6%. According to this basic description, we found that the Colombian investment fund industry is heavily weighted toward fixed income funds (debt and money market), which account for more than 75% of the number of the funds and more than 50% of the total assets managed by investment funds.

Based on the data obtained in the technical reports from June 2009 to December 2015, we were able to extract from that data source information on portfolio funds' compositions classified by type of income, type of asset, industry sector, and country of investment. The following figures and tables provide this information.

Figures 2 and 2.1 depict the weight in percentages of the portfolio fund composition of investment funds in Colombia classified by type of income. Table 4 provides summary statistics on portfolio fund composition by type of income. Panel A provides the historical evolution in percentage of portfolio funds composition by type of income, and Panel B provides summary statistics in percentage of fund composition by type of income.

Figure 2 and Figure 2.1: Weight in percentage of the portfolio funds composition classified by type of income, based on technical reports from June 2009 to December 2015.

Figure 2
Web Chart Average % of Porfolio Funds composition classified by type of income.
Based on technical reports from June 2009 - December 2015

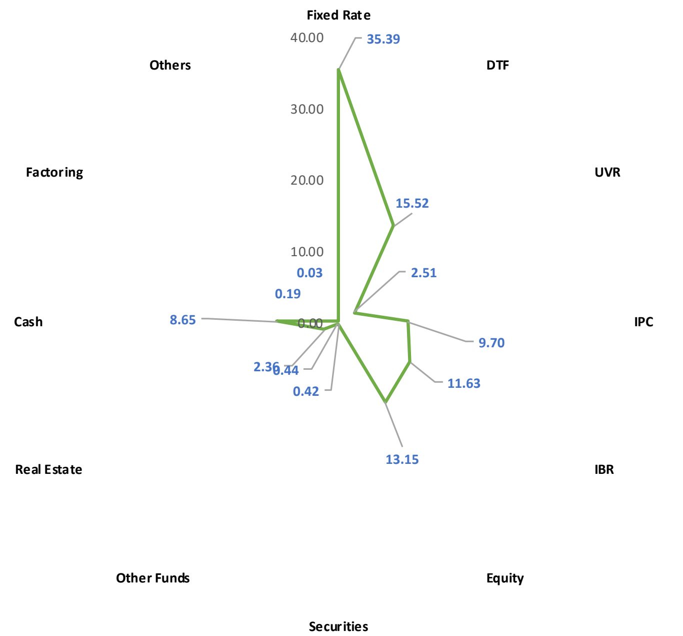
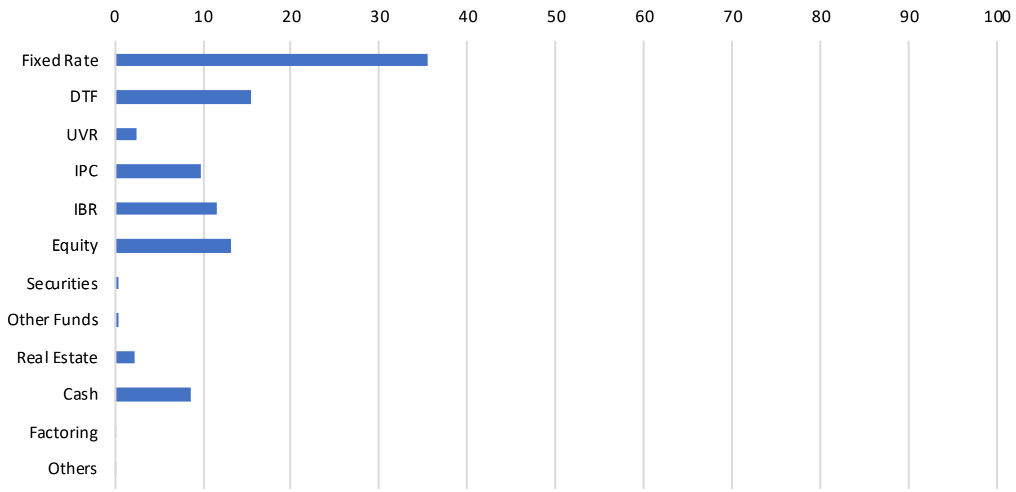


Figure 2.1
Average % of Porfolio Funds composition classified by type of income. Based on technical reports from June 2009 - December 2015



For the purpose of portfolio fund composition by type of income, the definitions for each type of income is as follows (for further references, see Appendix 3 – Indices Definition). The fixed rate is the type of income associated with securities assets in the Colombian markets that are priced at a fixed rate of interest and that regularly follow the COLTES.[25] DTF is an interest rate composite calculated as the weighted average of the interest rates on 90-day certificates of deposits (CDs) offered by Colombian banks and financial institutions. UVR ("*Unidad de Valor Real*" in Spanish) is an index that has been designed to provide investors with the general evolution of the mortgage market in Colombia, which can be used to measure Colombian Government bonds, or "B TES securities linked to UVR." IBR is the reference index employed to follow the development of the Colombian money market. IBR replicates an investment that produces the overnight IBR rate (interbank rate) that is calculated and published daily by the Central Bank. Equity is the reference that represents portfolio fund investments in companies listed on the Colombian stock exchange. Securities is the reference that represents portfolio fund investments in different types of securities in the Colombian market without being provided more details on the type of security. Other funds are the reference that represents portfolio fund investments in other investment funds. Real estate is the reference that represents portfolio fund investments in real estate assets. Cash is the reference that represents portfolio fund investments held in cash. Factoring is the reference that represents portfolio fund

[25] The Colombian Securities Exchange (BVC) has developed a series of total return indices weighted by market capitalization on Colombian Government debt bonds in COP (Colombian pesos). This index is the COLTES Government bond index. For further references, see Appendix 3.

investments comprised through purchases of account receivables. Others is the reference that represents portfolio fund investments that are not framed in the previous descriptions.

Table 4: Summary statistics: Mean of portfolio fund composition by type of income and summary statistics of portfolio fund composition by year.

Panel A: Summary statistics: Historical evolution in percentage of portfolio funds composition by type of income.

Fund composition by Type of Income	2009	2010	2011	2012	2013	2014	2015
Fixed Rate	39.45	31.10	36.02	38.57	40.24	34.67	28.06
DTF	27.67	24.59	12.69	18.65	17.49	12.73	7.51
UVR	3.06	2.14	2.49	2.47	2.33	2.35	2.97
IPC	4.43	8.78	9.22	8.31	9.91	12.21	10.11
IBR	3.87	7.23	16.37	11.61	8.57	14.82	12.35
Equity	8.37	13.05	13.90	14.03	14.04	14.03	11.02
Securities	0.17	0.03	0.22	0.45	0.73	0.59	0.20
Other Funds	0.18	0.09	0.09	0.30	0.53	0.35	1.10
Real Estate	4.10	3.01	2.15	1.56	1.13	3.06	3.05
Cash	7.78	9.34	6.24	3.93	4.82	5.13	23.59
Factoring	0.88	0.61	0.39	0.05	0.15	0.05	0.01
Others	0.00	0.00	0.20	0.04	0.00	0.00	0.02

Panel B: Summary statistics in percentage of portfolio fund composition by type of income

Fund composition by Type of Income	N	mean	sd	min	p25	p50	p75	max
Fixed Rate	9087	35.39	32.50	0.00	10.93	25.59	50.00	100.00
DTF	9087	15.52	16.30	0.00	0.00	12.36	27.52	85.34
UVR	9087	2.51	10.20	0.00	0.00	0.01	1.63	91.00
IPC	9087	9.70	14.18	0.00	0.00	6.55	15.18	100.00
IBR	9087	11.63	13.15	0.00	0.00	7.26	21.14	66.00
Equity	9087	13.15	31.80	0.00	0.00	0.00	0.00	100.00
Securities	9087	0.42	2.76	0.00	0.00	0.00	0.00	30.79
Other Funds	9087	0.44	2.51	0.00	0.00	0.00	0.00	58.00
Real Estate	9087	2.36	14.87	0.00	0.00	0.00	0.00	100.00
Cash	9087	8.65	15.14	0.00	0.00	0.00	12.24	100.00
Factoring	9087	0.19	1.49	0.00	0.00	0.00	0.00	25.47
Others	9087	0.03	0.59	0.00	0.00	0.00	0.00	24.55

Table 4: Panel A presents the historical evolution of the average portfolio fund composition classified by type of income used in the subsequent analyses. Panel B presents the summary statistics of the portfolio fund compensation and the number of observations for each type of income. The definitions for each type of income is as follows: Fixed rate is the type of income associated to securities assets in the Colombian markets that are priced at a fixed rate interest and regularly follows the COLTES. DTF is an interest rate composite, calculated as the weighted average of the interest rates on 90- day Certificates of Deposits (CDs) offered by Colombian banks and financial institutions. UVR (Unidad de Valor Real) is an index that has been designed to provide

investors the general evolution of the mortgage market in Colombia, which can be used to measure the Colombian Government bonds “B TES securities linked to UVR”. IBR is the reference index employed to follow the development of the Colombian Money Market. It replicates an investment that produces the Overnight IBR rate (Inter Bank Rate) that is calculated and published by the Central Bank daily. Equity is the reference to represent the portfolio fund investments in companies listed in the Colombian stock exchange. Securities is the reference to represent the portfolio fund investments in different type of securities in the Colombian market without given more detail of the type of security. Other funds are the reference to represent portfolio fund investments in other investment funds. Real Estate is the reference to represent the portfolio fund investments in real estate assets. Cash is the to reference to represent the portfolio fund investments that are held in cash. Factoring is the reference to represent the portfolio fund investments that are comprised in the purchasing of account receivables. Others is the reference to represent the portfolio fund investments that are not framed in the previous descriptions.

As Panels A and B in Table 4 indicate, the portfolio fund composition by type of income corresponds to, on average, approximately 35% of investments tied to fixed rates—a percentage that has been consistent during the sample period. In addition, portfolio investments tied to time deposit/money market assets (DTF) represent approximately 15%. This percentage has been consistent during the sample period; however, during 2015, the investments associated with this type of income were reduced to approximately 7%. We may infer the same conclusion from portfolio investments tied to inflation rates (IPC) and money market incomes (IBR) because during the sample period the average composition of investment funds were represented by this type of assets at 10% and 11%, respectively. These percentage were consistent during the sample period. Regarding equity investments, we observe that, on average, only approximately 13% of portfolio investments correspond to equity income and, during the sample period, this type of asset grows only slightly. In addition, portfolio investments in cash are important because they represent an average of approximately 9% of the composition of total portfolio funds. The percent of the portfolio that is in cash varies over the sample period, from approximately 3% to 23%, depending on the fund manager’s strategy. According to the composition of the investment fund by type of income, we observe that the Colombian investment fund industry is heavily weighted toward fixed income assets (money market and fixed rate), which account for more than 74% of the total asset portfolio. On average, only 13% of the portfolio is represented by companies (equity) and 9% is held in cash to balance the portfolio.

The portfolio funds’ composition by type of income as described in technical reports does not exactly reflect portfolio holdings of investment funds in Colombia because the breakdown of portfolio holdings for each fund is very broad and imprecise. Moreover, advisory companies are not obliged to report the securities that they hold but only broad categories such as income or cash. We believe that these data might be good approximations to infer—based on these broad weights—an asset class that is underlined by this type of income. In our case, this information is very useful because each individual type of income can be assigned a passive benchmark of broad asset classes to represent the investment opportunity set defined by advisory companies in their prospectuses or technical reports. This set can then be compared with a more robust benchmark that we customize in chapter 4.

Figures 3 and 3.1 provide the weight in percentage of the portfolio fund composition classified by type of asset. Table 5 provides the summary statistics of fund composition by type of asset. Panel A indicates the historical evolution in percentage of portfolio fund composition by type of asset, and Panel B indicates the summary statistics in percentage of fund composition by type of asset.

Figure 3 and Figure 3.1: shows the weight in percentage of the portfolio funds composition classified by type of asset, based on technical reports from June 2009 to December 2015.

Figure 3
Web Chart of Average % of Portfolio Funds Composition classified by type of Asset from June 2009 through December 2015

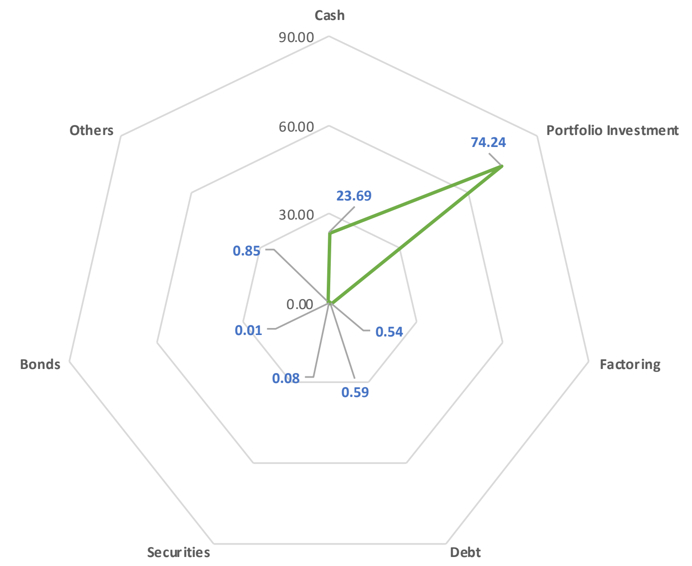


Figure 3.1
% of Portfolio Funds Composition classified by type of Asset from June 2009 through December 2015

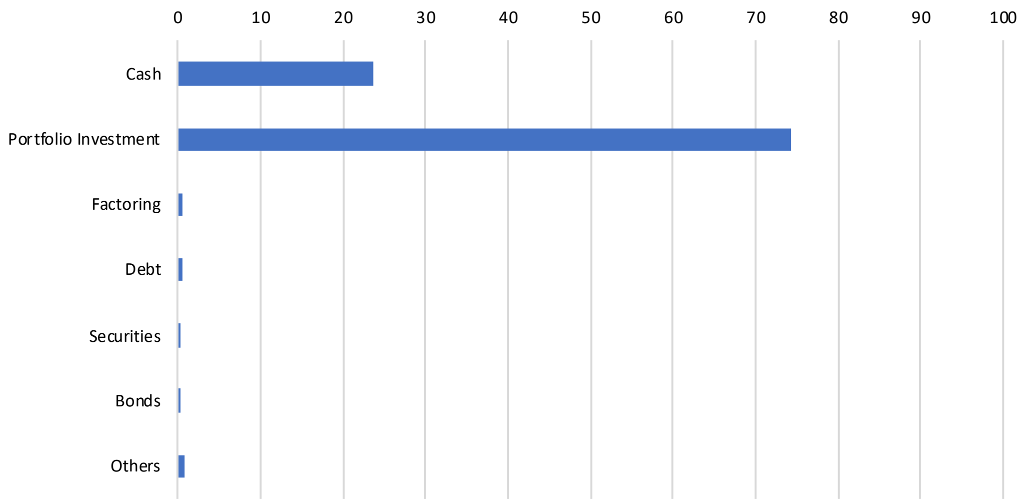


Table 5: Summary statistics: Mean of portfolio fund composition by type of asset and summary statistics of fund composition by year.

Panel A: Summary statistics: Historical evolution in percentage of portfolio funds composition by type of asset.

Fund composition by Type of Asset	2009	2010	2011	2012	2013	2014	2015
Cash	22.13	21.18	21.84	21.41	23.61	25.02	27.44
Portfolio Investment	76.91	78.25	76.46	76.74	73.63	71.93	70.92
Factoring	0.17	0.25	0.23	0.30	0.39	0.99	0.86
Debt	0.00	0.00	0.30	0.54	1.28	1.02	0.00
Securities	0.00	0.00	0.03	0.05	0.14	0.19	0.00
Bonds	0.00	0.00	0.00	0.05	0.00	0.00	0.00
Others	0.79	0.32	1.13	0.92	0.95	0.84	0.77

Panel B: Summary statistics in percentage of portfolio fund composition by type of asset

Fund composition by Type of Asset	N	mean	sd	min	p25	p50	p75	max
Cash	9087	23.69	15.20	0.00	11.09	24.45	35.00	100.00
Portfolio Investment	9087	74.24	17.32	0.00	63.79	73.77	87.81	100.00
Factoring	9087	0.54	3.73	0.00	0.00	0.00	0.00	42.13
Debt	9087	0.59	6.23	0.00	0.00	0.00	0.00	95.13
Securities	9087	0.08	0.99	0.00	0.00	0.00	0.00	23.34
Bonds	9087	0.01	0.26	0.00	0.00	0.00	0.00	8.39
Others	9087	0.85	4.04	0.00	0.00	0.00	0.00	54.40

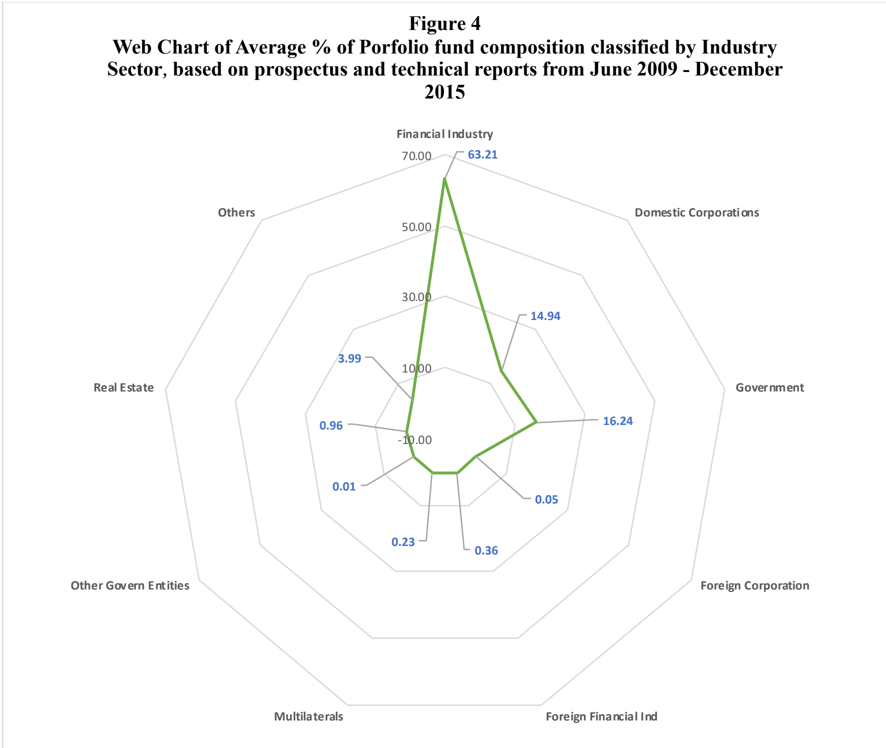
Table 5: Panel A presents the historical evolution of the average portfolio fund composition classified by type of asset. Panel B presents the summary statistics of the portfolio fund compensation and the number of observations for each type of asset.

These data do not provide much insightful information on how portfolio investments are classified by type of asset because company advisories report that, on average, 74% of investor money is invested in portfolio investments without additional details being provided on the type of asset. This percentage has been consistent during the sample period. In addition, on average, approximately 23% of portfolio holdings are represented in cash. If we compare this information with the data shown in Figure 2 and 2.1, and Table 4, this percentage is consistent with that of the portfolio composition by type of income, for which approximately 74% of the total investment is heavily weighted toward fixed income assets (money market and fixed rate). Although this information is inconclusive, we might state that, based on technical reports, the majority of investor money in the investment fund industry in Colombia is invested in money market assets instead of equity funds or more aggressive portfolio strategies.

The information deficiencies reported by company advisors regarding portfolio holdings show that necessary improvements must be made to provide stronger requirements for the disclosure of clear and sufficient information directed to investors—not only by the company advisory but also Colombia's SEC—to give investors sufficient information on the type of asset in which their money is invested.

Figure 4 and 4.1. indicate the weight in percentage of the portfolio fund composition classified or grouped by industry sector in Colombia, and Table 6 provides the summary statistics of this portfolio fund composition. Panel A indicates the historical evolution in percentage of portfolio fund composition, and Panel B provides the summary statistics in percentage of fund composition.

Figure 4 and Figure 4.1: Weight in percentage of the portfolio funds composition classified by industry sector, based on technical reports from June 2009 to December 2015.



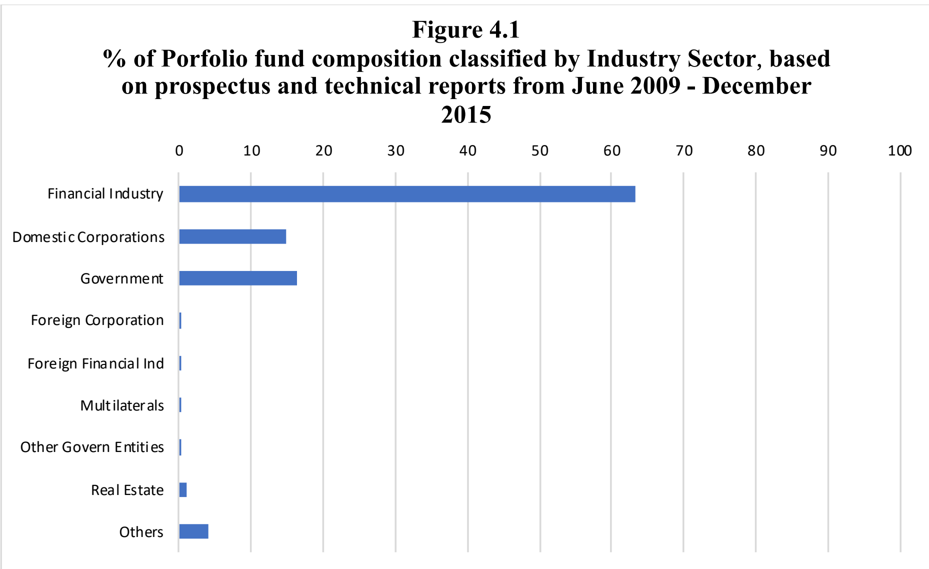


Table 6: Summary statistics: Mean of portfolio fund composition classified by industry sector and summary statistics of fund composition by industry sector

Panel A: Summary statistics: Historical evolution in percentage of portfolio fund composition classified by industry sector.

Fund composition by Type of Sector	2009	2010	2011	2012	2013	2014	2015
Financial Industry	71.66	65.03	56.51	62.59	61.47	61.30	69.43
Domestic Corporations	6.54	12.10	19.57	16.37	15.63	14.33	14.01
Government	17.88	19.69	16.94	15.30	15.88	17.41	13.58
Foreign Corporation	0.00	0.00	0.01	0.05	0.14	0.07	0.02
Foreign Financial Ind	0.64	0.59	0.21	0.28	0.52	0.33	0.20
Multilaterals	0.38	0.21	0.46	0.19	0.36	0.15	0.01
Other Govern Entities	0.00	0.00	0.03	0.03	0.00	0.00	0.00
Real Estate	2.00	1.47	1.96	0.81	0.00	1.14	0.75
Others	0.90	0.91	4.28	4.35	5.99	5.25	1.99

Panel B: Summary statistics in percentage of portfolio fund composition grouped by industry sector

Fund composition by Type of Sector	N	mean	sd	min	p25	p50	p75	max
Financial Industry	9087	63.21	35.67	0.00	30.00	80.63	91.24	100.00
Domestic Corporations	9087	14.94	29.21	0.00	0.00	0.10	7.00	100.00
Government	9087	16.24	23.86	0.00	0.58	8.89	17.84	100.00
Foreign Corporation	9087	0.05	0.43	0.00	0.00	0.00	0.00	7.72
Foreign Financial Ind	9087	0.36	2.10	0.00	0.00	0.00	0.00	26.78
Multilaterals	9087	0.23	1.40	0.00	0.00	0.00	0.00	16.74
Other Govern Entities	9087	0.01	0.16	0.00	0.00	0.00	0.00	4.24
Real Estate	9087	0.96	9.11	0.00	0.00	0.00	0.00	95.10
Others	9087	3.99	16.79	0.00	0.00	0.00	0.00	100.00

Table 6: Panel A presents the historical evolution of the average portfolio fund composition classified by industry sector. Panel B presents the summary statistics of the portfolio fund compensation and the number of observations for each group of industry sector.

As is observed, on average, approximately 63% of the portfolio investments in Colombia during the sample period were addressed toward assets issued by financial institutions, 15% approximately toward securities issued by domestic companies, and 16% toward securities issued by the Colombian Government. During the sample period, the percentage in these three main institutions was relatively consistent. Portfolio managers indicate a preference to purchase financial assets in the financial sector, of local companies, and the government. Purchases of financial assets in financial institutions and the local government are preferable during the sample period. If we compare these results with information obtained in the previous figures and tables, we continue to find that the Colombian investment fund industry is heavily weighted toward fixed income investments (such as DTF and IBR: both are references for money market assets) and risk-free investment assets (T-bills in Colombia), which account for, on average, more than 79% of the total assets managed by investment funds.

Finally, Figure 5 indicates the weight in percentage of the portfolio fund composition classified by country of investment (see Figure 5). Table 7 provides the summary statistics of such a portfolio fund composition. Panel A indicates the historical evolution in percentage of portfolio fund composition by country, and Panel B indicates the summary statistics in percentage of such fund composition.

Figure 5 and Figure 5.1: Weight in percentage of the portfolio funds composition grouped by country of investment, based on technical reports from June 2009 to December 2015.

Figure 5
Web Chart of Average % of Portfolio Funds Composition by Country, based on prospectus and technical reports from June 2009 - December 2015

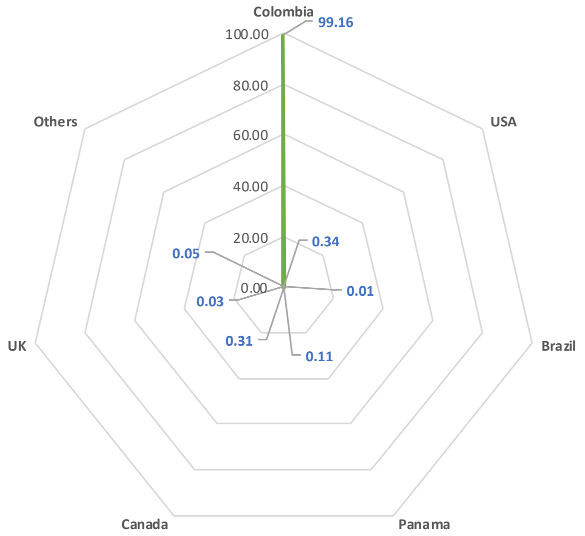


Figure 5.1
% of Portfolio Funds composition by Country, based on prospectus and technical notes from June 2009 - December 2015

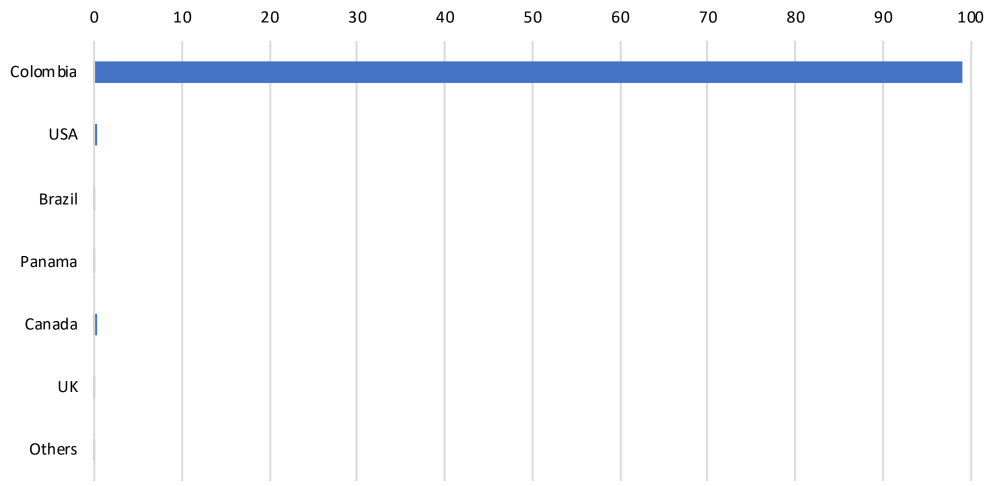


Table 7: Summary statistics: Mean of portfolio fund composition grouped by country of investment and summary statistics of fund composition by country.

Panel A: Summary statistics: Historical evolution in percentage of portfolio fund composition classified by country of investment.

Fund composition by Type of Country	2009	2010	2011	2012	2013	2014	2015
Colombia	99.18	98.91	98.87	99.24	99.19	99.44	99.02
USA	0.61	0.58	0.13	0.24	0.39	0.43	0.26
Brazil	0.00	0.00	0.00	0.01	0.02	0.01	0.00
Panama	0.06	0.00	0.00	0.01	0.01	0.03	0.54
Canada	0.00	0.52	0.88	0.48	0.30	0.07	0.03
UK	0.00	0.00	0.12	0.01	0.02	0.00	0.04
Others	0.15	0.00	0.00	0.01	0.07	0.03	0.11

Panel B: Summary statistics in percentage of portfolio fund composition grouped by country of investment.

Fund composition by Type of Country	N	mean	sd	min	p25	p50	p75	max
Colombia	9087	99.16	3.45	46.13	100.00	100.00	100.00	100.00
USA	9087	0.34	2.09	0.00	0.00	0.00	0.00	51.68
Brazil	9087	0.01	0.06	0.00	0.00	0.00	0.00	1.38
Panama	9087	0.11	0.68	0.00	0.00	0.00	0.00	5.21
Canada	9087	0.31	2.05	0.00	0.00	0.00	0.00	31.62
UK	9087	0.03	0.44	0.00	0.00	0.00	0.00	12.67
Others	9087	0.05	0.41	0.00	0.00	0.00	0.00	7.29

Table 7: Panel A presents the historical evolution of the average portfolio fund composition classified by country of investment. Panel B presents the summary statistics of the portfolio fund compensation and the number of observations for each country of investment.

As is observed, on average, approximately 99% of portfolio investments in Colombia during the sample period are in Colombia. This finding is consistent with what has been discussed in the preceding paragraphs because we have excluded from the sample investment funds with foreign investment strategies. Moreover, this percentage was consistent during the sample period.

The information obtained from these data sources and the style classification provided by the regulator do not assist us in inferring investment managers' strategies and do not explain the differences in future returns among funds or even provide useful benchmarks for evaluating relative past performance. Therefore, knowing more about how well investment funds in this market performed and the factors that account for the differences in their performance is important. This study also helps understand whether the failure to explicitly incorporate one or more indices for other types of fixed income, debt, or equity instruments in an analysis in emerging markets affects the interpretation of investment fund performance results and will develop appropriate performance evaluation models for investment funds (e.g., Sharpe, 1992; Blake et al., 1993; Brown and Goetzmann, 1997).

The dataset merged includes information on daily and monthly returns, management fees, exit and loading fees, size, net flows, turnover, characteristics of investment funds and advisors, whether a fund invests primarily in equity, debt, or the money market, and whether a fund is open- or closed-end.

We believe that this dataset is the most comprehensive ever prepared and used to study investment fund performance in Colombia in terms of both number of funds and number of attributes. This unique data set allows us to investigate the management styles for performance measurement and compensation and the links among fund performance, fund attributes, and management fees, as defined in the advisory contract. To the best of our knowledge, this topic has not been studied previously in the case of Colombia.

4.3. Main variables

To capture different aspects of fund attributes, we construct the measures and variables presented in Panels A, B, and C of Table 8. Panel A of Table 8 represents the historical evolution of average values from all of the variables. Panel B presents the summary statistics of the variables, and the number of observations for each variable is given under the condition that the data for all of the main variables should not be missing. Panel C presents the correlation matrix of all of the variables.

Table 8: Summary statistics: Mean variables sample period and Summary statistics of all variables

Panel A: Summary statistics: Historical evolution of average values (Mean variables)

Variables	2009	2010	2011	2012	2013	2014	2015
Effective fee rate (% annual)	1.664	1.703	1.789	1.772	1.727	1.730	1.706
Cole´s incentive rate	-0.008	-0.007	-0.006	-0.005	-0.005	-0.005	-0.002
Weighted incentive rate	0.997	0.997	0.998	0.998	0.998	0.998	0.999
Incentive ratio	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Concave linear dummy	0.011	0.009	0.007	0.006	0.006	0.006	0.003
Performance based fee dummy	0.137	0.140	0.135	0.155	0.158	0.159	0.169
Front Load Fees dummy	0.021	0.026	0.030	0.041	0.046	0.055	0.045
Back Load Fees dummy	0.334	0.333	0.343	0.323	0.312	0.319	0.294
Fund return before fee (% monthly)	0.666	0.400	0.189	0.510	0.179	0.205	0.114
Fund TA (COP Million)	234,668.12	213,942.35	207,894.12	235,402.79	259,944.39	274,675.77	326,453.98
Ln (Fund TA)	11.151	10.907	10.713	10.640	10.757	10.762	10.955
Family TA (COP$ Million)	2,137,050.05	2,124,974.28	2,098,393.60	2,434,046.64	2,573,194.34	2,766,076.19	3,115,201.79
Ln (Family TA)	13.808	13.763	13.748	13.855	13.869	13.962	14.082
Fund return volatility_30d	0.061	0.063	0.101	0.098	0.099	0.108	0.105
Fund return volatility_12m		0.429	0.412	0.558	0.663	0.770	0.607
Net money inflow (COP Million)	673.70	1,256.17	2,574.77	2,827.48	468.48	1,631.54	564.13
New Money Inflow (%)	0.045	0.211	0.069	0.083	0.023	0.023	0.012
Turnover	0.157	0.155	0.136	0.120	0.156	0.179	0.222
Open-end Closed-end Funds	0.979	0.971	0.955	0.939	0.924	0.914	0.928
Advisory Age (months)	297.505	290.186	279.311	274.881	274.116	274.556	274.680
Fund Age (months)	188.764	170.640	150.234	137.704	132.000	128.362	133.925
Ln (Fund Age)	5.114	4.974	4.788	4.664	4.603	4.563	4.601
Minimum required invesment (COP Million)	1,215.56	1,044.28	601.39	436.47	856.11	924.44	926.76
Ln (Minimum Investment)	13.545	13.604	13.801	14.028	14.312	14.465	14.445
Average account size (COP Million)	908.69	581.03	554.51	914.35	2,165.16	1,613.75	1,740.55
Ln (Account Size)	4.617	4.654	4.681	4.782	4.867	4.870	4.876
TER (% annual)	1.694	1.649	1.794	2.114	2.324	2.283	2.170
TER (% monthly)	0.140	0.136	0.148	0.174	0.190	0.187	0.178
Q/Max	0.483	0.481	0.507	0.549	0.587	0.590	0.627
Ln (Q/Max)	-1.071	-1.047	-0.930	-0.795	-0.688	-0.690	-0.654
Sub-Advisory Management Fund	0.000	0.000	0.004	0.009	0.012	0.012	0.012
Manager Postgraduate Certific dummy	0.674	0.691	0.617	0.610	0.615	0.627	0.653
Manager Master Education dummy	0.421	0.394	0.397	0.444	0.446	0.430	0.480
Manager gender	0.729	0.829	0.801	0.811	0.845	0.833	0.850
Tenure Manager (years)	10.656	10.694	11.246	11.243	11.274	10.973	10.436
Ln Tenure Manager (months)	4.753	4.755	4.817	4.819	4.832	4.798	4.729
Selection Return	0.060	-0.010	-0.052	0.017	0.037	-0.061	-0.047
Alpha rolling estimation Sharpe			-0.065	0.031	0.034	-0.049	-0.057
Alpha rolling estimation Prospectus			-0.155	-0.132	-0.006	-0.134	-0.020
Alpha rolling estimation Carhart			-1.163	-0.578	-1.451	-0.651	-1.923
Alpha single estimation Sharpe	0.005	0.003	0.003	-0.014	-0.014	-0.013	-0.015
Alpha single estimation Prospectus	-0.070	-0.083	-0.096	-0.112	-0.100	-0.092	-0.081
Alpha single estimation Carhart	-0.025	-0.205	-0.494	-0.700	-0.820	-0.837	-0.867
Sensitivity flow-to-Performance_selection	0.001	0.001	0.001	0.000	-0.001	-0.001	-0.001
Sensitivity flow-to-Performance_Prospectus	-0.006	-0.006	-0.006	-0.007	-0.007	-0.007	-0.007
Sensitivity flow-to-Performance_Sharpe	0.001	0.001	0.000	0.000	0.000	0.000	0.000

Panel B: Summary statistics of all variables

Variables	N	mean	sd	min	p25	p50	p75	max
Effective fee rate (% annual)	11301	1.733	0.974	0.015	1.210	1.500	2.000	8.000
Cole´s incentive rate	11301	-0.005	0.065	-0.800	0.000	0.000	0.000	0.000
Weighted incentive rate	11301	0.998	0.025	0.694	1.000	1.000	1.000	1.000
Incentive ratio	11301	1.000	0.000	1.000	1.000	1.000	1.000	1.000
Concave linear dummy	11301	0.007	0.081	0.000	0.000	0.000	0.000	1.000
Performance based fee dummy	11301	0.152	0.359	0.000	0.000	0.000	0.000	1.000
Front Load Fees dummy	11301	0.040	0.196	0.000	0.000	0.000	0.000	1.000
Back Load Fees dummy	11301	0.321	0.467	0.000	0.000	0.000	1.000	1.000
Fund return before fee (% monthly)	11301	0.294	1.332	-12.910	0.218	0.312	0.459	13.483
Fund TA (COP Million)	11301	253,018.76	669,889.03	0.37	11,592.79	63,045.19	217,200.76	8,962,909.45
Ln (Fund TA)	11301	10.809	2.020	-0.992	9.358	11.052	12.289	16.009
Family TA (COP$ Million)	11301	2,505,443.60	2,893,572.33	14.34	334,059.68	1,411,399.23	3,266,765.62	11,535,563.84
Ln (Family TA)	11301	13.879	1.521	2.663	12.719	14.160	14.999	16.261
Fund return volatility_30d	11301	0.094	0.253	0.000	0.005	0.008	0.023	3.707
Fund return volatility_12m	8981	0.599	1.279	0.008	0.053	0.093	0.283	8.517
Net money inflow (COP Million)	11301	1491.924	57844.436	-1933035.873	-2035.336	-0.336	2935.683	1534075.843
New Money Inflow (%)	11301	0.063	1.174	-1.006	-0.039	0.000	0.043	94.359
Turnover	11301	0.161	0.502	0.000	0.006	0.047	0.159	14.428
Open-end Closed-end Funds	11301	0.940	0.238	0.000	1.000	1.000	1.000	1.000
Advisory Age (months)	11301	278.912	91.188	44.000	282.000	291.000	291.000	476.000
Fund Age (months)	11301	144.319	96.044	22.000	62.000	114.000	254.000	357.000
Ln (Fund Age)	11301	4.717	0.744	3.091	4.127	4.736	5.537	5.878
Minimum required invesment (COP Million)	11301	822.49	3,900.15	0.00	0.20	0.50	5.00	33,369.34
Ln (Minimum Investment)	11028	14.091	3.359	0.000	12.206	13.122	15.425	24.231
Average account size (COP Million)	11301	1,276.06	8,468.03	0.00	34.65	94.01	371.90	265,780.28
Ln (Account Size)	11285	4.78	1.92	-4.32	3.55	4.55	5.92	12.49
TER (% annual)	8808	2.098	1.540	0.010	1.380	1.620	2.460	13.790
TER (% monthly)	8808	0.172	0.123	0.001	0.114	0.134	0.203	1.082
Q/Max	11301	0.555	0.278	0.000	0.329	0.575	0.787	1.000
Ln (Q/Max)	11301	-0.810	0.820	-7.719	-1.112	-0.554	-0.239	0.000
Sub-Advisory Management Fund	11301	0.008	0.089	0.000	0.000	0.000	0.000	1.000
Manager Postgraduate Certific dummy	11251	0.636	0.481	0.000	0.000	1.000	1.000	1.000
Manager Master Education dummy	11251	0.432	0.495	0.000	0.000	0.000	1.000	1.000
Manager gender	11251	0.821	0.383	0.000	1.000	1.000	1.000	1.000
Tenure Manager (years)	11168	10.972	4.416	2.000	8.000	10.000	15.000	25.000
Ln Tenure Manager (months)	11168	4.791	0.441	3.178	4.564	4.787	5.193	5.704
Selection Return	11301	-0.013	0.759	-10.286	-0.101	-0.025	0.090	12.653
Alpha rolling estimation Sharpe	6980	-0.020	0.718	-10.514	-0.107	-0.029	0.076	8.353
Alpha rolling estimation Prospectus	6980	-0.083	0.829	-10.559	-0.303	-0.082	0.160	8.453
Alpha rolling estimation Carhart	802	-1.168	2.645	-13.585	-2.496	-0.770	0.185	7.773
Alpha single estimation Sharpe	11301	-0.008	0.265	-2.008	-0.062	-0.030	0.014	0.969
Alpha single estimation Prospectus	11301	-0.093	0.273	-2.126	-0.144	-0.075	-0.022	0.918
Alpha single estimation Carhart	1377	-0.685	0.786	-2.777	-1.337	-0.456	-0.092	0.634
Sensitivity flow-to-Performance_selection	11300	0.000	0.006	-0.007	-0.004	-0.002	0.002	0.048
Sensitivity flow-to-Performance_Prospectus	11300	-0.007	0.004	-0.011	-0.010	-0.008	-0.005	0.028
Sensitivity flow-to-Performance_Sharpe	11300	0.000	0.001	-0.002	0.000	0.000	0.001	0.003

Panel C: Correlation matrix of the variables

Variables	Effective fee rate (% annual)	Cole´s incentive rate	Weighted incentive rate	Concave linear dummy	Performance based fee dummy	Front Load Fees dummy	Back Load Fees dummy	Fund return before fee (% monthly)	Fund TA (COP Million)	Ln (Fund TA)	Family TA (COP$ Million)	Ln (Family TA)	Fund return volatility_30d	Fund return volatility_12m	Net money inflow (COP Million)	New Money Inflow (%)	Turnover	Open-end Closed-end Funds	Advisory Age (months)	Fund Age (months)	Ln (Fund Age)	Minimum required invesment (COP Million)	Ln (Minimum Investment)	Average account size (COP Million)	Ln (Account Size)	TER (% annual)	TER (% monthly)	Q/Max	Ln (Q/Max)	Sub-Advisory Management Fund	Manager Postgraduate Certific dummy	Manager Master Education dummy	Manager gender	Tenure Manager (years)	Selection Return	Alpha rolling Sharpe	Alpha rolling Prospectus	Alpha rolling Carhart	Sensitivity flow-to-Performance_selection	Sensitivity flow-to-Performance_Prospectus	Sensitivity flow-to-Performance_Sharpe
Effective fee rate (% annual)	1.000																																							
Cole´s incentive rate	-0.793	1.000																																						
Weighted incentive rate	-0.793	1.000	1.000																																					
Concave linear dummy	0.793	-1.000	-1.000	1.000																																				
Performance based fee dummy	-0.897	0.802	0.802	-0.802	1.000																																			
Front Load Fees dummy	-0.751	0.349	0.349	-0.349	0.769	1.000																																		
Back Load Fees dummy	0.919	-0.906	-0.906	0.906	-0.957	-0.594	1.000																																	
Fund return before fee (% monthly)	0.552	-0.418	-0.418	0.418	-0.145	-0.142	0.310	1.000																																
Fund TA (COP Million)	-0.939	0.938	0.938	-0.938	0.914	0.643	-0.949	-0.466	1.000																															
Ln (Fund TA)	-0.805	0.911	0.911	-0.911	0.628	0.302	-0.778	-0.754	0.882	1.000																														
Family TA (COP$ Million)	-0.932	0.904	0.904	-0.904	0.946	0.716	-0.944	-0.378	0.992	0.817	1.000																													
Ln (Family TA)	-0.887	0.917	0.917	-0.917	0.918	0.679	-0.914	-0.355	0.984	0.821	0.993	1.000																												
Fund return volatility_30d	-0.494	0.386	0.386	-0.386	0.354	0.604	-0.272	-0.506	0.549	0.528	0.568	0.609	1.000																											
Fund return volatility_12m	-0.732	0.275	0.275	-0.275	0.726	0.993	-0.553	-0.154	0.585	0.251	0.658	0.609	0.550	1.000																										
Net money inflow (COP Million)	0.906	-0.653	-0.653	0.653	-0.685	-0.512	0.793	0.707	-0.764	-0.766	-0.717	-0.645	-0.248	-0.532	1.000																									
New Money Inflow (%)	0.940	-0.658	-0.658	0.658	-0.697	-0.682	0.746	0.777	-0.829	-0.813	-0.801	-0.754	-0.598	-0.682	0.923	1.000																								
Turnover	-0.871	0.884	0.884	-0.884	0.713	0.512	-0.794	-0.719	0.932	0.966	0.894	0.899	0.697	0.458	-0.754	-0.877	1.000																							
Open-end Closed-end Funds	0.826	-0.400	-0.400	0.400	-0.799	-0.986	0.661	0.246	-0.689	-0.381	-0.747	-0.695	-0.555	-0.989	0.642	0.770	-0.566	1.000																						
Advisory Age (months)	0.747	-0.465	-0.465	0.465	-0.897	-0.836	0.777	-0.104	-0.658	-0.262	-0.724	-0.666	-0.144	-0.832	0.568	0.538	-0.383	0.857	1.000																					
Fund Age (months)	0.808	-0.424	-0.424	0.424	-0.857	-0.971	0.711	0.099	-0.690	-0.330	-0.757	-0.705	-0.435	-0.970	0.606	0.690	-0.504	0.982	0.937	1.000																				
Ln (Fund Age)	0.173	-0.196	-0.196	0.196	-0.898	-0.963	0.773	0.137	0.200	0.406	0.241	0.321	-0.163	-0.213	-0.015	-0.006	-0.205	0.979	0.205	0.962	1.000																			
Minimum required invesment (COP Million)	-0.877	0.569	0.569	-0.569	0.597	0.675	-0.632	-0.821	0.759	0.772	0.732	0.692	0.688	0.678	-0.858	-0.985	0.856	-0.751	-0.440	-0.645	-0.146	1.000																		
Ln (Minimum Investment)	-0.952	0.661	0.661	-0.661	0.889	0.911	-0.826	-0.410	0.880	0.649	0.909	0.871	0.616	0.894	-0.771	-0.885	0.788	-0.946	-0.819	-0.927	-0.322	0.849	1.000																	
Average account size (COP Million)	-0.899	0.497	0.497	-0.497	0.769	0.740	-0.772	-0.459	0.704	0.535	0.705	0.617	0.227	0.773	-0.921	-0.864	0.597	-0.841	-0.799	-0.833	-0.316	0.797	0.863	1.000																
Ln (Account Size)	-0.320	0.236	0.236	-0.236	0.934	0.895	-0.868	0.113	0.219	0.167	-0.326	-0.459	-0.345	-0.305	0.028	0.064	-0.099	-0.942	-0.167	-0.325	-0.339	0.415	0.388	0.809	1.000															
TER (% annual)	-0.779	0.349	0.349	-0.349	0.816	0.901	-0.693	-0.074	0.609	0.256	0.668	0.593	0.236	0.922	-0.657	-0.658	0.398	-0.938	-0.955	-0.972	0.180	0.593	0.865	0.892	-0.303	1.000														
TER (% monthly)	-0.779	0.354	0.354	-0.354	0.820	0.902	-0.697	-0.070	0.612	0.257	0.672	0.598	0.237	0.922	-0.655	-0.656	0.399	-0.938	-0.958	-0.973	-0.957	0.591	0.858	0.890	0.940	1.000	1.000													
Q/Max	-0.980	0.846	0.846	-0.846	0.963	0.759	-0.964	-0.405	0.969	0.779	0.975	0.943	0.469	0.724	-0.825	-0.859	0.851	-0.815	-0.806	-0.827	-0.881	0.780	0.944	0.841	0.946	0.783	0.785	1.000												
Ln (Q/Max)	-0.956	0.697	0.697	-0.697	0.957	0.860	-0.909	-0.301	0.881	0.618	0.909	0.859	0.412	0.845	-0.804	-0.830	0.723	-0.911	-0.907	-0.931	-0.960	0.754	0.964	0.907	0.996	0.911	0.912	0.970	1.000											
Sub-Advisory Management Fund	-0.908	0.570	0.570	-0.570	0.918	0.904	-0.837	-0.229	0.793	0.490	0.835	0.774	0.372	0.903	-0.762	-0.788	0.616	-0.949	-0.941	-0.971	0.166	0.718	0.955	0.920	-0.094	0.966	0.966	0.917	0.986	1.000										
Manager Postgraduate Certific dummy	-0.729	0.925	0.925	-0.925	0.624	0.311	-0.735	-0.630	0.880	0.963	0.832	0.865	0.635	0.234	-0.592	-0.707	0.958	-0.348	-0.225	-0.304	-0.109	0.679	0.618	0.376	-0.085	0.177	0.180	0.741	0.562	0.426	1.000									
Manager Master Education dummy	-0.800	0.881	0.881	-0.881	0.934	0.491	-0.970	-0.101	0.874	0.666	0.877	0.856	0.113	0.441	-0.653	-0.563	0.662	-0.543	-0.773	-0.634	0.438	0.427	0.710	0.650	-0.018	0.626	0.631	0.885	0.828	0.756	0.648	1.000								
Manager gender	-0.985	0.742	0.742	-0.742	0.869	0.704	-0.909	-0.545	0.885	0.759	0.872	0.811	0.358	0.703	-0.952	-0.926	0.802	-0.800	-0.761	-0.791	0.469	0.850	0.913	0.948	-0.568	0.802	0.802	0.953	0.946	0.909	0.643	0.795	1.000							
Tenure Manager (years)	0.712	-0.945	-0.945	0.945	-0.682	-0.346	0.763	0.491	-0.895	-0.917	-0.864	-0.904	-0.621	-0.257	0.518	0.639	-0.926	0.363	0.293	0.344	0.003	-0.600	-0.625	-0.338	-0.132	-0.205	-0.209	-0.756	-0.583	-0.449	-0.986	-0.708	-0.615	1.000						
Selection Return	0.039	-0.216	-0.216	0.216	0.120	-0.028	-0.109	0.465	-0.202	-0.403	-0.179	-0.264	-0.811	0.040	-0.121	0.204	-0.469	-0.035	-0.426	-0.167	0.159	-0.321	-0.087	0.299	0.118	0.374	0.372	-0.015	0.129	0.210	-0.550	0.220	0.105	0.519	1.000					
Alpha rolling Sharpe	0.047	-0.263	-0.263	0.263	0.172	0.114	-0.093	0.596	-0.203	-0.494	-0.150	-0.228	-0.717	0.173	-0.027	0.239	-0.505	-0.143	-0.520	-0.282	0.154	-0.346	-0.024	0.282	0.119	0.459	0.459	0.000	0.174	0.274	-0.598	0.212	0.075	0.540	0.971	1.000				
Alpha rolling Prospectus	-0.783	0.650	0.650	-0.650	0.668	0.307	-0.810	-0.471	0.671	0.651	0.620	0.542	-0.110	0.329	-0.919	-0.708	0.572	-0.450	-0.584	-0.481	0.164	0.589	0.592	0.838	0.105	0.589	0.588	0.742	0.719	0.672	0.463	0.753	0.865	-0.417	0.412	0.289	1.000			
Alpha rolling Carhart	0.560	-0.700	-0.700	0.700	-0.334	0.121	0.589	0.726	-0.572	-0.825	-0.465	-0.439	-0.012	0.129	0.749	0.595	-0.665	0.017	0.036	-0.011	0.131	-0.523	-0.284	-0.446	0.145	-0.038	-0.037	-0.496	-0.341	-0.221	-0.682	-0.515	-0.601	0.595	0.047	0.244	-0.787	1.000		
Sensitivity flow-to-Performance_selection	0.771	-0.362	-0.362	0.362	-0.833	-0.923	0.695	0.035	-0.622	-0.250	-0.688	-0.620	-0.273	-0.936	0.617	0.638	-0.403	0.947	0.965	0.984	0.969	-0.575	-0.865	-0.861	-0.941	-0.997	-0.997	-0.788	-0.913	-0.966	-0.192	-0.636	-0.783	0.231	-0.337	-0.438	-0.544	-0.006	1.000	
Sensitivity flow-to-Performance_Prospectus	0.779	-0.373	-0.373	0.373	-0.839	-0.927	0.702	0.045	-0.633	-0.263	-0.698	-0.632	-0.287	-0.938	0.621	0.647	-0.417	0.951	0.965	0.987	0.973	-0.585	-0.873	-0.862	-0.946	-0.996	-0.997	-0.796	-0.918	-0.969	-0.207	-0.641	-0.789	0.246	-0.323	-0.424	-0.544	0.001	1.000	1.000	
Sensitivity flow-to-Performance_Sharpe	0.855	-0.498	-0.498	0.498	-0.893	-0.957	0.769	0.151	-0.747	-0.406	-0.806	-0.753	-0.438	-0.952	0.662	0.734	-0.566	0.977	0.941	0.996	0.999	-0.681	-0.944	-0.860	-0.978	-0.968	-0.970	-0.874	-0.960	-0.987	-0.373	-0.690	-0.839	0.410	-0.156	-0.256	-0.543	0.075	0.979	0.982	1.000

Table 8: Panel A presents the historical evolution of average values for all the variables used in the subsequent analyses. Panel B presents the summary statistics of the variables and the number of observations for each variable is given under the condition that the data on all the main variables should be non-missing. The definitions for each variable are provided in the Appendix 1. Panel C presents the correlation matrix of the variables.

As Panel A of Table 8 indicates, little variation exists in those variables across time in our sample, although some variables, such as Fund TA, have been growing steadily. This finding is consistent with what has been mentioned about the growth of the mutual fund industry in Colombia in recent years, where they have played an extremely important role in financial markets.

The definitions of the variables are provided in Appendix 2. However, the variables and measures that we construct to capture different aspects of fund attributes are explained as follows.

4.3.1 Dependent variables

Fund return: The dependent variable of this study is the return perceived by the investment fund. The fund return is a function of the advisory fund's effort, noise, and ability to select adequate portfolio managers (Deli, 2002; Ma, Tang, and Gomez, 2012). The fund return is obtained from the electronic database collected from the Colombian SEC, which captures the daily return of each investment fund from 2009 to 2015. Thus, we construct the performance fund on a monthly basis, which is determined based on the difference between the first and last total units' portfolio of the month divided by the first total units' portfolio of the month.

4.3.2. Independent variables

Fee rate (TER): Advisory companies are required to disclose in the prospectus agreement the percentage of commission fees and characteristics of the investment fund.

We use information in the fund advisory contract and monthly reports to observe aspects of the slope and shape of the compensation contract between advisory companies and investors. We build on the literature that has studied advisory compensation to measure the following incentive variables (the slope and shape of the compensation contracts) and used it as a proxy for actual incentives received by fund companies (Coles, Suay, and Woodbury, 2000; Deli, 2002; Deli and Varma, 2002; Kuhnen, 2004; and Warner and Wu, 2004; Massa et al., 2009).

The fee rate is defined as the compensation rate paid by investors to the advisory fund on the basis of the fund's current total assets. The fee rate was hand-collected from the total dataset of monthly reports and legal prospectuses of each investment fund. The specified compensation for advisory firms is typically a fee rate between 1.2% and 2% on the base of the total assets managed by the fund and the fund's performance. On average, the effective fee rate is approximately 1.7% during the sample period. This compensation fee rate in our sample is stable over time.

Total fund expenses are comprised of the fee rate and other operating costs, such as administration and accounting costs, taxes, and agent fees. The advisory company deducts these expenses on a monthly basis from the fund's assets. The fee rate plus the aforementioned expenses are usually expressed as total annual expenses as a fraction of total asset funds under management, also known as the total expense ratio (TER) (Gil Bazo et al., 2009). For funds without an available expense ratio, we use the fee rate. The total expense ratio is hand-collected through each fund's monthly reports. On average, the total effective rate is approximately 2% during the sample period, which—in our sample—has grown by an average of 4% from 2009 to 2015.

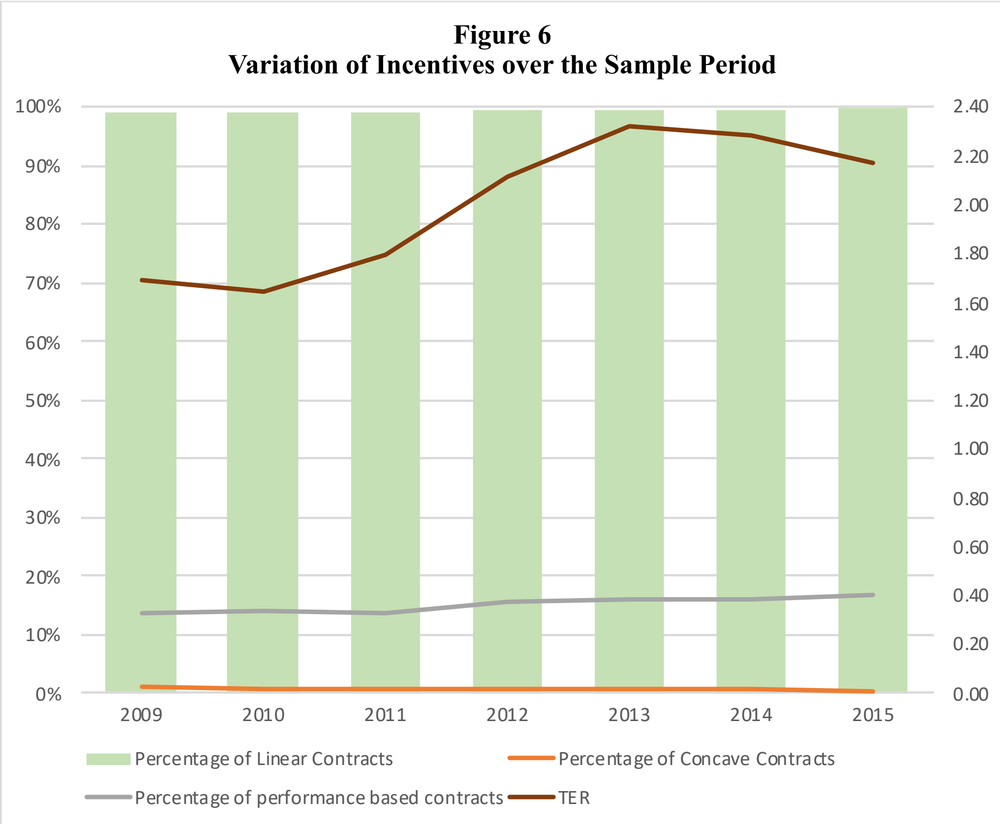
For contractual incentives that change based on total assets, we follow Massa et al. (2009) by calculating incentives on the basis of the concavity of the contract. This measure is called *Coles' incentive rate* and is defined as the difference between the last and first marginal compensation rates divided by the fee rate. This measure takes the value of 0 for linear contracts and negative values for concave contracts, with the incentive increasing as this variable increases. We use *Coles' incentive rate* for the shape of the compensation contract (Massa et al., 2009). As stated by Massa et al. (2009), this incentive measure considers only the first and last fee rates rather than the entire shape of the contract. Thus, we also use an alternative measure of incentives called *Weighted incentive rate*; that is, we weight the Coles' incentive rate as the ratio of the weighted average of the marginal compensation rates to the first applicable marginal compensation rate. This measure of concavity is equal to 1 for a linear contract and less than 1 for a concave contract. The third measure of contractual incentives, following the methodology of Massa et al. (2009: page 1784), is to capture the potential losses and gains from changes in total assets around the current total assets of the fund. This measure is called the *incentive ratio (IR)*, which is defined as the ratio of the fee rate that would apply because of a 10% increase in total assets compared with the fee rate that would apply because of a 10% decrease in total assets. We also use a dummy variable *LinearConcaveD* to measure concavity, which takes the value of 1 for funds with linear contracts and 0 for funds with concave contracts, to test for the robustness of our results. An increase in any of these three measures reflects an increase in incentives.

The sixth measure of incentives is constructed to account for contractual incentives that are based on performance-based fees (*performance-based fee*). This measure takes the value of 1 for contracts that a have an incentive fee on a percentage based on the fund's performance and 0 otherwise.

The simplicity and specificity of the contracts enable me to examine how fixed and variable compensation differs across advisory firms over time and how a fund's performance is affected based on these incentive compensations.

As shown in Figure 6 and Table 8, in our sample, the use of linear contracts is approximately 100% and is stable over time. The *Coles' incentive ratio* on average is –0.005 and is stable over the sample period. Therefore, less than 1% over the sample period is concave contracts. Concave contracts are virtually inexistent in the investment fund industry in Colombia. In addition, the *weighted incentive rate* is, on average, almost equal to 1 (0.998) and stable over time, confirming the linearity of the contracts. The rest of the variables defined to measure concave contracts have the same results (see Table 8, Panels A and B), that is, linearity of contracts.

Figure 6: Variations of incentives in the investment fund industry in Colombia over the sample period.



This figure shows variations of incentives in the investment fund industry in Colombia over the sample period. The figure illustrates the no variation of percentage of funds that have linear fee structure over the sample period. It also plots the cross-sectional averages of Coles' incentive rate measure, the percentage of performance-based contracts and the TER (in percentage) over the sample period.

In approximately 15% of the funds during the sample period, performance-based compensation is tied to their own performance. The percentage of performance-based compensation over the years slightly increases. Finally, the TER is not stable over time but increases considerably as of the year 2010. Thus, the total expense ratio, which is available for most of the observations, becomes the more relevant variable in our analysis to study the link between performance and commission fees, given that almost 100% of TER and the effective fee rate is associated with linear contracts and only 15% of the funds tie compensation to performance.

Risk taking: We construct the fund's total risk as the total volatility of lagged fund returns for the 12 months of a calendar year. For observations of a fund that represent less than 12 months, we construct the total volatility as the lagged fund returns of the six months of a calendar year. A fund's net return data are obtained from the variable fund return previously described.

Size of the fund (fundTA): A fund's size is a potentially useful measure of uncertainty concerning ability and is measured as the total asset value of the fund's portfolio. The fund's size measures the total assets under management of the investment advisor and is also defined as the natural logarithm of the total assets managed by this advisor.

The *fund flow (or new money inflow)* during a month is approximated from the daily returns and the total asset values under the assumption that all new money is invested between the beginning and the end of a month. New money is defined as the percentage growth in total assets under management (in local currency) between the beginning and the end of month t, or the net of internal growth (assuming reinvestment of returns or dividends) as follows (Ferreira et al., 2012):

$$\boldsymbol{New\ money\ inflow_{i,t}} = \frac{(\boldsymbol{FundTA_{i,t}} - \boldsymbol{FundTA_{i,t-1}}) - \boldsymbol{R_{i,t}}}{\boldsymbol{FundTA_{i,t-1}}}$$

where $\boldsymbol{FundTA_{i,t}}$ represents the total assets in local currency of fund *i*, and $\boldsymbol{R_t}$ represents the assumed returns or dividends of fund *i* in local currency.

Funds have an average flow of 0.06% per month, but the net flow has not been stable over time. In our sample, the net flow has been decreasing from 2009 to 2015 and, in aggregate, has been positive.

Following Dahlquist et al. (2000: page 420), we use “two different measures of trading activity. The first measure is turnover, which we calculate as the minimum of purchases and sales divided by the fund size. This definition allows us to capture the active management of the portfolios, and not just whether a fund is growing or shrinking.” The second measure is the effective fee rate paid by the fund (trading costs) and the total expense ratio previously described.

Turnover (turnover ratio) as previously mentioned is defined as the fund’s minimum sales or purchases divided by its total assets (Dahlquist et al., 2000; Massa et al., 2009; Ferreira et al., 2012). Considering that this variable has been neither considered by the regulator in Colombia nor is reported by the investment fund, it needs to be estimated.

To estimate *Turnover*, the first assumption is that sales can be defined as any decrease in total fund assets and purchases as any increase in total fund assets. An increase is denoted as *Money flowIn* and a decrease as *Money flowOut*. If we calculate the difference between the daily total assets in local currency of fund *i* on day *t* and total assets in local currency of fund *i* on day *t–1* and then subtract the returns or dividends reinvested into fund *i*, we can estimate the daily *Money flowIn* and *Money flowOut*. Through this approach, a positive difference on day *t* is assumed to be *Money flowIn* for fund *i*, that is, a purchase. A negative difference on day *t* is assumed to be *Money flowOut* for fund *i*, that is, a sale. This approach allows us to approximate the monthly purchases and sales for funds *i* during month *t*. Given the absence of this variable in the investment fund industry in Colombia, we believe that the following approach is a good proxy for estimating *Turnover* as a measure of trading activity:

$$\boldsymbol{Turnover\ (estimated)_{i,t}} = \frac{\boldsymbol{Min\ [Money\ FlowIn_{i,t}\,,\ Money\ FlowOut_{i,1}]}}{\boldsymbol{FundTA_{i,t}}}$$

Based on our estimation, the average *turnover* is 16% and is not stable over time. From 2009 to 2013, *turnover* decreases but slightly increases from 2014 to 2015. This result indicates that investment funds in Colombia are not too active.

Funds often charge loads, which are one-time fees used to pay distributors (Gil-Bazo and Luis-Verdu, 2009). These loads are defined as a *Front Load Fee* and *Back Load Fee* and are expressed as a percentage of the assets invested. These loads are paid at the time of purchasing (*Front Load*) or redeeming (*Back Load*) a fund's securities. We use *Front Load Fee* and *Back Load Fee* as dummy variables to measure these loads. *Front Load Fee* takes the value of 1 if the fund has a front load in the contract and 0 otherwise. *Back Load Fee* takes the value of 1 if the fund has a back load in the contract and 0 otherwise.

As shown in Table 8, loads paid at the time of purchasing securities (*Front Load*) are on average 4% and stable over time. Loads paid at the time of redeeming securities (*Back Load*) are on average 32% and are also stable over time.

Notice that all returns used in the evaluation are gross returns, that is, before fees or commissions, exit/loading fees, and taxes.

4.3.3. Control variables

Fund Characteristics:

Fund Age: the number of years that the fund has traded. This information is obtained from a database maintained by the Colombian SEC and monthly reports.

Family size: measured as the sum of all assets under management by a particular company.

Average Account Size[26]: the ratio of the TA to the number of investor accounts as reported by the investment funds.

Colombian fund characteristics can be compared with those of U.S. funds. Local funds' characteristics, such as fees, portfolio turnover, and trading activities, are comparable for U.S. funds (e.g., Ippolito, 1992 and Pozen, 1998; Dahlquist et al., 2000). Passive management fees in the United States, as noted by Dahlquist et al. (2000: page 412), "are about 50% lower than traditional active management fees." We believe that Colombian funds are similar to passive funds; however, in contrast to passive funds in the United States and consistent with previous research (see Dahlquist et al., 2000), their fees are similar to those of active U.S. funds. However, overall, we cannot provide clear evidence that the funds in our sample are similar to U.S. funds.

Advisor Characteristics:

Age of the investment company fund: This measure is used because investors should know more about the ability of older organizations. Age is calculated based on the first date that investment advisors register before the Superintendence of Finance.

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26 From Colombian' SEC information electronically gathered, we know the number of portfolio accounts of an investment fund (i.e., the number of investors in the fund). The TA divided by the number of investors provides the size of an average investor account.

We also use a dummy variable, *Open-end and Closed-end Funds*, to measure whether the mutual funds in Colombia are open-end or closed-end. This variable takes the value of 1 if the fund is open-end and 0 otherwise. On average, funds in Colombia are 94% open-end funds and 6% closed-end funds.

Manager Characteristics:

Tenure experience: The information on managerial tenure industry experience is hand-collected through technical reports. Thus, industry experience measures how long (in years) a manager has worked for an investment company and how long a manager has managed investment funds. The average managerial tenure for the investment funds is 10 years and stable over time.

Manager education. The information on managerial education is hand-collected through technical reports. This variable is an indicator of the manager's level of education and is a control variable because management education can affect the average performance of investment funds. We use *Manager advance course* and *Manager master education* as dummy variables to measure the level of education. *Manager advance course* takes the value of 1 if the manager has obtained only a professional degree or a specialization course, and 0 otherwise. *Manager master education* takes the value of 1 if the manager has obtained, in addition to a professional degree, a master's or Ph.D. degree, and 0 otherwise.

We also use a dummy variable, *Manager gender*, to measure the manager's gender, which takes the value of 1 if the manager is male and 0 if the manager is female.

For investment fund managers in Colombia, an average 64% have only a professional degree or specialization course, and 43% have a master's or Ph.D. degree. In addition, 82% of managers are male, and the rest are female.

We create a dummy variable called *Sub Advisory Fund*, which captures whether the fund is managed by more than one person or by a team. The variable takes the value of 1 if the fund is managed by more than one person or by a team, and 0 otherwise. The prospectuses and technical documents of all funds indicate that approximately 99% of funds are managed by one manager, and a small fraction of the funds are listed as team managed.

4.3.4. Individual indices – Benchmarks

As was previously explained in section 3.2, the information hand-collected through the prospectuses and technical reports of each investment fund enables us to classify the investment funds' objectives into the following categories: i) money market, ii) equity, iii) debt, iv) balanced, and iv) real estate (see Table 3). Thus, this classification of investment funds and the classification provided by the regulator do not tell us anything about the strategies of advisory companies and do not provide us with useful benchmarks for evaluating relative past performance. Investments in fixed income securities (debt and money market funds) in Colombia constitute a major part of the investment fund industry, but we have almost no information on their performance.

In the performance evaluation, our objective is to compare the return on a fund with the return on a benchmark that captures the closest passive strategy to the fund. To that end, we use traded indices of major asset classes to determine how effectively individual fund managers have performed their functions and the extent to which value has been added through active management (Sharpe, 1992). As in Dahlquist et al. (2000), for tractability and to facilitate interpretations, we use returns on broad asset classes to represent the investment opportunity set.

For this analysis, we first analyzed sixteen indices: Colombian short- and long-term treasury bills (COLTES, COLTES CP, COLTES LP, COLTES UVR); various indices for fixed income securities in Colombia (COLIBR, TCC, DTF); inflation index rate in Colombia (COCPI); U.S. Dollar–Colombian Peso exchange rate index (TRM Index); bond index of all types of fixed income instruments, including sovereign bonds, investment grade corporate bonds, and high yield bonds across developed and emerging markets (LEGATRUU); various equity indices in the Colombian stock market (COLEQTY, COLSC, COLCAP, COLIR); a foreign equity index that captures large and mid-cap companies across 23 developed and emerging markets (ACWI); and a real estate asset index in the Colombian market (PEI). All of these indices are obtained from the Central Bank, the Colombian SEC, the stock exchange, and Bloomberg. Appendix 3 describes the asset classes and sixteen indices analyzed for the associated return series. Summary statistics of all indices are described in Table 9.

Table 9: Summary Statistics of all indices

Index	N	mean	sd	min	p25	p50	p75	max
r_coltes	84	0.723	1.613	-3.807	-0.495	0.839	1.767	5.261
r_coltescp	84	0.617	0.886	-1.792	0.022	0.626	1.140	3.109
r_colteslp	84	0.795	2.268	-5.676	-0.833	0.937	2.409	5.916
r_coltesuvr	84	0.722	1.303	-4.196	0.155	0.667	1.454	4.776
r_dtf_index	84	0.376	0.087	0.282	0.325	0.359	0.417	0.774
r_colibr_index	84	0.342	0.088	0.231	0.270	0.337	0.387	0.705
r_tcc_rate	84	0.326	0.084	0.229	0.270	0.290	0.353	0.600
r_cocpi_index	84	0.276	0.283	-0.260	0.090	0.240	0.480	1.150
r_trm_index	84	0.466	3.863	-10.003	-1.710	0.266	2.290	10.288
r_legatruu	84	0.209	1.511	-3.807	-0.703	0.318	1.238	3.568
r_coleqty_index	84	0.564	4.371	-9.104	-2.718	0.160	3.558	11.082
r_colcap_index	84	0.463	4.518	-9.107	-2.599	-0.145	3.633	11.018
r_colsc_index	84	0.013	4.227	-11.727	-3.044	0.333	2.210	12.785
r_colir_index	84	0.609	4.527	-9.259	-2.637	0.360	3.776	11.096
r_acwi_index	84	0.771	4.982	-11.382	-2.287	1.091	3.757	12.778
r_pei_index	84	0.387	1.437	-3.488	0.664	0.916	1.063	2.791
smb	84	-0.002	0.038	-0.085	-0.026	-0.001	0.024	0.100
hml	84	0.000	0.025	-0.065	-0.013	-0.004	0.014	0.080
wml	84	0.004	0.033	-0.116	-0.009	0.003	0.023	0.087

This table presents the summary statistics of the indices used for the associated return series and the number of observations for each index is given under the condition that the data on all the indices should be non-missing. The Fama and French risk factors (Fama and French, 1993) and the momentum factor was kindly provided Pedraza et al (2017) and constructed by these authors for the stock market in Colombia during our sample period. These risk factors provided: SMB (small stocks minus large stocks) and HML (high book-to-market stocks minus low book-to-market stocks) portfolios, and the returns-to-price momentum portfolio WML (winners minus losers), allow us to regress the Colombian equity investment fund on the three Fama-French risk factors and the momentum factor, to analyze investment fund performance (Carhart, 1997). The definitions for the other indices are provided in Appendix 3.

When a strong correlation is present among the indices and to avoid heteroskedasticity and multicollinearity across funds, we eliminate from the model those indices to avoid introducing systematic errors into the regression models. Thus, we do not include in our analysis the indices COLTESCP, COLTESLP, DTFINDEX, COLEQTYINDEX, COLSCINDEX, AND COLIRINDEX, because these indices present a high correlation among COLTES, COLIBR, and COLCAP, respectively. In addition, we have eliminated from our model the index ACWIINDEX and TRMINDEX because they reference investments carried out abroad. In this study, we consider only funds with investments in Colombia. Table 10 describes the index correlation.

To capture developments in the debt market, from the previously described sixteen indices, we used only six debt indices (consisting of both government and mortgage bonds and money market indices) provided by the Central Bank and Bloomberg. The following government and mortgage bond indices have an average duration of between one and five years: COLTES, COLTESUVR, COCPI, and LEGATRUU. In addition, the other group is a money market index (COLIBR, TCC) consisting of (approximately) 90-day certificates of deposits and the overnight interbank (IBR) rate published daily by the Central Bank. The COLIBR and TCC indices have been used as important benchmarks in Colombia to measure money market assets. The returns on the COLTES benchmark rate are used as a proxy for a risk-free investment.

To capture developments in the stock market, from the previously described sixteen indices, we used only the COLCAP return on four equity indices mentioned (COLCAP, COLSC, COLEQTY, and ACWI). COLCAP is a market capitalization-weighted index that includes the 20 most liquid stocks on Colombia's Stock Exchange.

To capture developments in the real estate market, we used PEI, the real estate asset index in the Colombian market.

Table 10: Indices correlation

	r_coltes	r_coltescp	r_colteslp	r_coltesuvr	r_dtf_index	r_cocpi_index	r_colibr_index	r_tcc_rate	r_legatruu	r_coleqty_index	r_colcap_index	r_colsc_index	r_colir_index	r_acwi_index	r_trm_index	r_pei_index	smb	hml	wml
r_coltes	1.000																		
r_coltescp	0.868	1.000																	
r_colteslp	0.960	0.822	1.000																
r_coltesuvr	0.633	0.457	0.686	1.000															
r_dtf_index	0.276	0.355	0.259	0.211	1.000														
r_cocpi_index	-0.161	-0.259	-0.124	-0.003	0.142	1.000													
r_colibr_index	0.267	0.297	0.253	0.209	0.910	0.189	1.000												
r_tcc_rate	0.266	0.333	0.273	0.116	0.696	-0.018	0.572	1.000											
r_legatruu	0.322	0.274	0.348	0.240	-0.115	-0.200	-0.160	0.155	1.000										
r_coleqty_index	0.304	0.290	0.325	0.235	0.103	-0.186	-0.024	0.274	0.442	1.000									
r_colcap_index	0.307	0.293	0.333	0.226	0.119	-0.180	0.002	0.287	0.443	0.990	1.000								
r_colsc_index	0.240	0.203	0.267	0.158	0.086	0.082	-0.016	0.253	0.169	0.616	0.607	1.000							
r_colir_index	0.310	0.295	0.332	0.238	0.108	-0.192	-0.014	0.269	0.454	0.998	0.989	0.596	1.000						
r_acwi_index	0.245	0.244	0.230	0.192	-0.069	-0.114	-0.158	0.062	0.547	0.454	0.433	0.230	0.452	1.000					
r_trm_index	-0.333	-0.261	-0.365	-0.255	0.064	0.047	0.145	-0.198	-0.605	-0.553	-0.551	-0.370	-0.554	-0.590	1.000				
r_pei_index	0.116	0.091	0.126	0.126	-0.022	-0.261	0.022	-0.080	0.007	-0.027	-0.052	-0.144	-0.011	0.098	-0.119	1.000			
smb	-0.170	-0.192	-0.179	-0.121	-0.093	0.165	0.027	-0.122	-0.388	-0.639	-0.634	-0.168	-0.652	-0.309	0.361	0.035	1.000		
hml	-0.044	-0.045	-0.051	-0.069	0.127	0.141	0.144	0.048	-0.349	-0.420	-0.420	0.121	-0.439	-0.253	0.284	-0.017	0.602	1.000	
wml	-0.042	0.022	-0.037	0.051	-0.058	-0.061	-0.120	-0.116	0.141	0.017	-0.028	-0.187	0.020	0.119	0.011	0.039	-0.374	-0.333	1.000

This tables presents the correlation matrix of the broad indices used for the associated return series. When a high correlation is present among the indexes and to avoid heteroscedasticity and multicollinearity across funds, we eliminate from the model those indices to not introduce systematic error into the regression models. Thus, we do not include in our analysis the indices coltescp, colteslp, dtf_index, coleqty_index, colsc_index and colir_index, because these indices present a high correlation among coltes, colibr, colcap, respectively. In addition, we have eliminated from our model the index acwi_index and trm_index, because those indices make reference to investment carry out abroad.

In addition to the index previously mentioned to capture developments in the stock markets in Colombia (COLCAP), Pedraza et al. (2017) kindly provided us with the Fama and French (1993) risk factors and the momentum factor constructed by these authors for the stock market in Colombia that covered our sample period. These risk factors were SMB (small stocks minus large stocks) and HML (high book-to-market stocks minus low book-to-market stocks) portfolios and the returns-to-price momentum portfolio WML (winners minus losers), allowing us to regress the Colombian equity investment fund on the three Fama–French risk factors, and the momentum factor for analyzing investment fund performance (Carhart, 1997). Table 9 provides the summary statistics of the risk factors described, and Table 10 describes the indices' correlation.

5. STYLE CLASSIFICATION AND BENCHMARK ANALYSIS

Investment fund performance is often evaluated by comparing the performance of the managed portfolio against the performance of a specific passive benchmark (e.g., S&P 500, among others). The performance attribution intends to explain the sources of the difference between the manager’s performance and the specified benchmark (Arik and Jagannathan, 2002); in other words, the manager should beat the passive benchmark.

One common approach to evaluating performance is the returns-based style analysis, which consists of extracting from the portfolio returns provided by the asset managers the maximum information possible on fund performance, strategy, and risk taking. The goal of this approach, as stated by Wermers (2011, page 541), involves “the application of the best possible econometric models, based on i) the application of proper benchmarks (types of risks taken by fund managers), ii) the breakdown of systematic versus idiosyncratic risks taken by the managers (selection of proper benchmarks and the detection of dynamic risk-taking strategies by managers), and iii) the statistical distribution of the returns to both systematic and idiosyncratic risks (that is, both can be nonnormally distributed).”

One of the advantages of this approach is that the return-based style analysis provides a way to identify the asset mix style of the fund manager and compare it with the asset mix style of the performance benchmark. This comparison allows investors to evaluate how well an “active money manager” performed and whether he provides diversification benefits by managing the portfolio (Arik and Jagannathan, 2002). Another advantage of this approach, as posited by

(Wermers, 2011), is that it does not fully depend on information provided by fund managers. This approach is useful in situations in which not much disclosed much information exists, such as in our case. In most cases, the fund returns are public data.

This approach has been applied to debt–stock portfolios with some success to infer—simply by studying the past returns—the types of securities held by a fund manager to explain the investment strategy of the asset managers. See, for example, Elton, Gruber, Das and Hlavka (1992); Sharpe (1992); Blake et al. (1993); Brown et al. (1997), Fung and Hsieh (2004); Barras et al. (2010).

However, the application of a proper style benchmark asset class is extremely important under this approach because the results of the evaluation of investment funds is very sensitive to the benchmark selected to evaluate the funds' ability to outperform a passive strategy (Blake et al., 1993; Brown and Goetzmann, 1997) and requires assumptions associated with the strategies made by fund managers that generate returns (Warmers, 2011). The inappropriate choice of style benchmarks may lead to inadequate inferences regarding performance and level of active management (Arik and Jagannathan, 2002). Thus, the most well-documented problem is the choice of inefficient benchmarks, giving rise to an ambiguously executed performance evaluation (Wermers 2011).

The other commonly used approach to evaluate performance is the use of a portfolio-based style analysis that consists of examining the portfolio composition of the funds and comparing the characteristics or attributes of the securities in which the manager has invested with the characteristics of the securities of the performance benchmark.

This approach has several advantages, as stated by Wermers (2011: page 550). First, this approach permits a more precise construction of a benchmark, avoiding the choice of inefficient benchmarks as in the return-based approach. Second, the fund's style may shift nontrivially during short periods (Wermers, 2011). Third, the portfolio's data composition facilitates the evaluation of fund manager capabilities before all costs because we can obtain important insights into asset allocation or security selection (Wermers, 2011, page 550). Fourth, the portfolio composition data provide additional insights into an explanation and assesses the sources of value added by a manager. Finally, the benchmark construction is more precise because this approach is applied on a security-by-security basis (Wermers, 2011).

Grinblatt and Titman (1989a) were the first to use the portfolio-based approach (or portfolio-holding) by applying portfolio weights from periodic SEC filings of U.S. mutual funds to evaluate fund performance. This study broke new ground by examining performance "using holdings applied to changes in the closing price quotations of stocks to compute the return of an asset manager" (Werners, 2011; page 551). Other academic researchers built on Grinblatt and Titman (1989a) with some success to develop portfolio performance measures and to use the portfolio weight to construct benchmarks (Wermers, 2011). See, for example, Grinblatt and Titman (1993); Ferson and Schadt (1996); Kothari and Warner (2001); and Wermers (2010).

However, the main disadvantage of this approach is that the portfolio composition—or the holding data—is not always available, making difficult the application of this approach.

For instance, in the U.S. market, investment funds are typically grouped according to the type of securities in which they invest and the style of the manager. Some of the common characteristics that are often used include i) for equity funds: market capitalization, book-to-market (price) ratio, historical earnings growth rate, dividend yield; and ii) for fixed income securities: duration, ratings, and others (Brown and Goetzmann, 1997; Arik and Jagannathan, 2002). The accessibility of this information makes possible the application of these two approaches with relative frequency.

Unfortunately, this information is not required by the regulator or advisory companies in Colombia. Company advisors and regulators in the Colombian local market rarely provide the type of securities in which they invest, but only broad categories such as income or cash, because their opinion is that providing these data reveals the investment fund’s strategy.

Given the absence of a more detail style classification by the regulator and advisory companies, we immersed ourselves into the legal prospectuses and technical reports of every fund to understand in greater detail their investment policy, asset classes, and some characteristics of the investment funds to complement the classification of the regulator and to obtain more information on the common attributes of investment funds, as described in detailed in section 3.2.

The advantage that we obtain by reading all of this information is that we can i) classify investment funds based on a basic description and compare it with the classification made by the regulator (see Table 3), ii) identify the appropriate broad indices as major asset classes (see Table 9), and iii) extract from the technical reports the portfolio fund composition classified by type of income or security (see Table 4).

This last point is extremely important because, although portfolio funds' composition by type of income described in the technical reports do not exactly reflect the portfolio holdings of investment funds in Colombia—because advisory companies are not obliged to report such information—we believe that these data are a good approximation to infer a broad asset class that is underlined from this type of income. However, this does not mean that we are able to apply the methodology based on portfolio holdings similar to Grimblatt and Titman (1989) because the breakdown of portfolio holdings that we have for each fund is very broad and imprecise.

The style classification that we obtain by reading the legal prospectuses and technical reports resulted in five types of funds: balanced funds, debt funds, equity funds, money market funds, and real estate funds (see Table 3 and section 3.2). However, this style classification based on the characteristics and investment policy of the funds involves substantial judgment. For example, an advisory firm typically has operations in several different sectors of the economy, and identifying how much of the investment fund goes into each sector may be difficult. In addition, portfolio compositions may change over time (Arik and Jagannathan, 2002).

In Colombia, because i) the type of securities in which funds invest resources is not publicly revealed, ii) the classification of investment funds provided by the regulator in Colombia tells us nothing about the strategies of investment managers, iii) and providing useful benchmarks for evaluating relative past performance does not help us, in this section, we first focus on analyzing the investment funds from 2009 to 2015 to identify styles and customized benchmarks from different style classifications. We focus in this manner because our ultimate goal is to evaluate whether investors have enough information to evaluate fund performance in the Colombian market.

Although other methodologies exist to estimate fund performance, such as portfolio holdings, the most suitable (or even feasible) in the Colombian case is the return-based approach. A return-based style analysis allows us to identify the management style and comparing it with the asset mix style of the performance benchmark without having full access to the composition data. We should customize benchmark returns to evaluate fund performance because the style fund classifications provided by the regulator do not assist in providing useful benchmarks for these purposes. We compare the empirically determined styles with the classifications provided by the regulator because no industry classification such as Morningstar exists in the Colombian market that we might use. Finally, we use the portfolio fund composition in Colombia classified by type of income to apply Sharpe's methodology based on mapping fund performance onto broad indices' returns as an alternative measure of determining performance benchmarks to permit power comparisons with the benchmark return calculated under the return-based style approach. We evaluate whether, with this information, investors are able to evaluate investment performance.

In the next chapter, we use the identified styles and customized benchmarks to evaluate the performance of investment funds in Colombia.

5.1. Style issues – Portfolio weights

The return-based style analysis showed that investment funds have been characterized traditionally according to parameters estimated using linear asset pricing methods to differentiate mutual funds on the basis of systematic risk characteristics; see, for example, Jensen (1968), Connor and Korajczyk (1986), Lehmann and Modest (1987), Grinblatt and Titman (1988, 1989), and (Werners, 2011). Quantitative methods for security aggregation were first employed by Elton and Gruber (1970), who developed a classification algorithm using a linear model of fundamental characteristics that proved useful for grouping securities and forecasting cross-sectional differences. Carleton and McGee (1970) developed switching regression and hierarchical clustering methods to aggregate financial assets. Connor and Korajczyk (1991) used an asymptotic principal component analysis to aggregate financial assets. Sharpe (1988, 1992) used quadratic programming to determine a fund's exposure to changes in the returns of major asset classes.

Brown and Goetzmann (1997) argued that single-factor and multifactor linear models are only correct when portfolio weights remain fixed throughout time and when the systematic risk characteristics of the securities held in the portfolio remain fixed as well. Active portfolio management affects performance measurements because linear risk models fail to properly rank fund managers when they change their asset weights throughout time; see, for example, Dybvig and Ross (1985); Connor and Korajczyc (1991); and Grinblatt and Titman (1993).

Brown and Goetzmann (1997) performed a cluster analysis and style classification algorithm that are consistent with asset pricing models to group funds based on the cross-sectional time series of past returns.

To avoid problems with style classification, Brown and Goetzmann (1997) suggested a procedure that accommodates nonlinear strategies by allowing factor loadings to change on a month-by-month basis. This technic compares the style categories formed in the space of past returns with alternate categorization schemes formed in the space of fixed factor loading.

We follow the methodology employed by Sharpe (1992), which provides a different style classification procedure that is widely used in the investment management industry; the methodology employed by Brown and Goetzmann (1997), which performed a cluster analysis on fund returns; and a style classification algorithm that determines a fund's exposure to changes in the return of major asset classes. Through these methodologies, we find evidence that the style classification employed allows us to group funds based on the cross-sectional time series of past returns and on the response to exogenously specified and endogenously determined stochastic variables (see Appendix 2 for variables definition and classification).

This evidence is consistent with the finance literature previously described because we do a better job of predicting cross-sectional variations in Colombian fund returns than do traditional linear model classifications. We also find that this classification captures major differences in manager behavior as manifested in the temporal patterns of returns (Brown and Goetzmann, 1977). As Brown et al.

(1997) showed, these classifications provide less information about the magnitude of fund loading on major macroeconomic factors but provide a useful means to identify widespread, common patterns in manager behavior.

5.2. Empirical methodology

The objective of our analysis is to use past returns to determine natural groupings of funds that have some predictive power in explaining the future cross-sectional dispersion in fund returns. Those groupings are referred to as styles.

5.2.1. Relation to multifactor or multibeta model

To measure exposures to variations in fund returns, we employ a multiple factor model that is commonly used to evaluate how major asset class factors affect the returns on individual securities and portfolios of securities.

The use of broad indices as major asset class factors has several advantages, as stated by Sharpe (1992). First, each category's profile has some intuitive interpretation: one group may be tilted toward bonds and fixed income assets, whereas another may be tilted toward stocks. Second, the procedure suffers less from the difficulty of heteroskedasticity across funds that introduces systematic errors into the regression models. Third, the coefficients have a natural interpretation as portfolios. The drawbacks are that the procedure does not allow for temporal variations in the portfolio weights (Brown et al., 1977).

In such models, a portfolio of factors is used to replicate as closely as possible the return on a security (Sharpe, 1992). The model specification is as follows:

$$\boldsymbol{R_{i,t}} = [\,\boldsymbol{\beta_{i,1}}\widetilde{\boldsymbol{F}}_{\boldsymbol{1,t}} + \boldsymbol{\beta_{i,2}}\widetilde{\boldsymbol{F}}_{\boldsymbol{2,t}} + \cdots + \boldsymbol{\beta_{i,n}}\widetilde{\boldsymbol{F}}_{\boldsymbol{n,t}}] + \widetilde{\varepsilon}_{\boldsymbol{i,t}} \qquad t=1,2,3\ldots T \quad (1)$$

where $\boldsymbol{R_i}$ represents the return on asset *i*, $\widetilde{\boldsymbol{F}}_{\mathbf{1}}$ represents the value of factor 1, $\widetilde{\boldsymbol{F}}_{\mathbf{2}}$ represents the value of factor 2, $\widetilde{\boldsymbol{F}}_{\boldsymbol{n}}$ represents the value of the $\boldsymbol{n^{th}}$ (last) factor, and $\widetilde{\varepsilon}_{i}$ represents the "nonfactor" component of the return on *i*. The coefficients $\boldsymbol{\beta}_{\boldsymbol{i},\mathbf{1}}, \boldsymbol{\beta}_{\boldsymbol{i},\mathbf{2}}, \dots \boldsymbol{\beta}_{\boldsymbol{i},\boldsymbol{n}}$ represent the exposure of selected securities *i* to the different set of industry- and economy-wide pervasive factors. The nonfactor returns for one asset $\widetilde{\varepsilon}_{i,t}$ are assumed to be uncorrelated with those of every other (e.g., $\widetilde{\varepsilon}_{j}$). In effect, the factors are the only sources of correlation among the returns. The $\boldsymbol{\beta}_{\boldsymbol{i},\mathbf{1}}\widetilde{\boldsymbol{F}}_{\mathbf{1},\boldsymbol{t}} + \boldsymbol{\beta}_{\boldsymbol{i},\mathbf{2}}\widetilde{\boldsymbol{F}}_{\mathbf{2},\boldsymbol{t}} + \cdots + \boldsymbol{\beta}_{\boldsymbol{i},\boldsymbol{n}}\widetilde{\boldsymbol{F}}_{\boldsymbol{n},\boldsymbol{t}}$ expression represents the particular combination (portfolio) of factors that best replicates the return $\widetilde{\boldsymbol{R}}_{\boldsymbol{i},\boldsymbol{t}}$.

In factor models, the portfolio weights $\boldsymbol{\beta}_{\boldsymbol{i},\mathbf{1}}, \boldsymbol{\beta}_{\boldsymbol{i},\mathbf{2}}, \dots \boldsymbol{\beta}_{\boldsymbol{i},\boldsymbol{n}}$ need not sum to 1, and a factor $\widetilde{\boldsymbol{F}}_{\boldsymbol{k},\boldsymbol{t}}$, need not necessarily be the return on a portfolio of financial assets (Arik and Jagannathan, 2002).

Equation (1) suggests a procedure to be used to calculate fund exposures. Given the monthly returns for a fund during the sample period, along with comparable returns for a selected set of asset classes, we simply employ a multiple regression analysis with fund returns as the dependent variable and asset class returns as the independent variables. The resulting slope coefficients are then interpreted as the fund's historical exposure to the asset class returns.

As stated by Sharpe (1992), an asset class factor model or return-based style analysis can be considered a special case of the generic factor model. In such a model, we replicate the performance of a managed portfolio during a specified period as best as possible using the return on a passively managed portfolio of style benchmark index portfolios. The two important differences in the factor models are: i) every factor is a return on a particular style benchmark index portfolio, and ii) the weights or sensitivities assigned to the factors are required to sum to 1 (Sharpe, 1992). Rewriting Equation (1) yields the following:

$$\boldsymbol{R_{i,t}} = [\,\boldsymbol{\varphi_{1,i} x_{1,t}} + \boldsymbol{\varphi_{2,i} x_{2,t}} + \cdots + \boldsymbol{\varphi_{n,i} x_{n,t}}] + \widetilde{\mathcal{E}}_{\boldsymbol{t,i}} \qquad \text{t=1,2,3…T} \quad (2)$$

where $\boldsymbol{R_{i,t}}$ represents the managed fund return at time *t* and $\boldsymbol{x_1}, \boldsymbol{x_2} \dots \boldsymbol{x_n}$ are the returns on the style benchmark index. The slope coefficients $\boldsymbol{\varphi_1}, \boldsymbol{\varphi_2}, \dots \boldsymbol{\varphi_n}$ represent the managed portfolio's average allocation among the different style benchmark index portfolios or asset classes during the selected period (Sharpe 1992; Ben Dor and Jagannathan 2002). The sum of the terms in the brackets represents the portfolio return that can be attributable by its exposure to the different style benchmarks and is termed the *style* of the manager. The residual component of the portfolio returns $\widetilde{\mathcal{E}}_{\boldsymbol{t,i}}$ reflects the manager's decision to depart from the benchmark composition within each style benchmark class. This is the return from *selection*, that is, the part of the return attributable to the manager's stock-picking ability (Sharpe 1988, 1992).

Considering the set of monthly returns for a managed investment fund along with the set of returns on the style benchmark index portfolios (asset classes), the portfolio weights or sensitivities, $\boldsymbol{\varphi_1}, \boldsymbol{\varphi_2}, \dots$, in Equation (2) can be estimated using a multivariate regression analysis. To obtain the slope coefficients that closely reflect the actual investment fund policy, it is important—as shown by Sharpe (1992)—to incorporate restrictions on the style benchmark weights. The following two restrictions are imposed as follows:

$$\boldsymbol{\varphi_{j,i}} \geq \mathbf{0}\ \forall\ \mathbf{j} \in \{\mathbf{1}, \mathbf{2}, \dots \mathbf{J}\}, \qquad (3)$$

$$\boldsymbol{\varphi_{1,i} + \varphi_{2,i} + \varphi_{J,i} = 1}, \tag{4}$$

For each fund *i*, the first restriction corresponds to the constraint that no benchmark can be sold short. The second restriction imposes the requirement that all wealth is invested in the available style benchmark.

Our final objective is to approximate managed fund returns as closely as possible using the return on a portfolio of passive style benchmark indices (Sharpe, 1992).

To this end, we select a set of coefficients that minimizes the "unexplained" variation in returns (i.e., the variance of $\widetilde{\varepsilon}_{t,i}$) subject to constraints (3) and (4). As shown by Sharpe (1988, 1992), the presence of these constraints requires the use of a quadratic programming algorithm in what is known as a *style analysis*. Rearranging Equation (2), we can express the time series of fund *i*, residual term $\widetilde{\varepsilon}_{t,i}$, as a function of the fund return and the return on the style benchmark. Then, for each fund *j*, the following constrained quadratic optimization problem solves for the optimal portfolio weight sensitivities that minimize the volatility of the residual:

$$\min_{\boldsymbol{\varphi}} \sum\nolimits_t \left[\left(\boldsymbol{R_{i,t}} - \boldsymbol{\overline{R}_i}\right) - \sum\nolimits_{j=1} \boldsymbol{\varphi_{i,j}}\left(\boldsymbol{x_{j,t}} - \boldsymbol{\overline{x}_j}\right)\right]^2 \tag{5}$$

$$\boldsymbol{0 \leq \varphi_{j,i} \leq 100}\%$$

$$\boldsymbol{\varphi_{1,i} + \varphi_{2,i} + \varphi_{J,i} = 1}$$

where $\boldsymbol{\varphi_{i,j}}$ in Equation (5) are the appropriate sensitivities or portfolio weights given that all weights are greater than zero and sum to 1; $\boldsymbol{x_1, x_2 \ldots x_J}$, are the returns on the style benchmark index; and $\boldsymbol{\overline{R}_i}$ and $\boldsymbol{\overline{x}_j}$ represent sample means.

Appendix 4 includes the Stata code used to implement this quadratic programming algorithm.

As Sharpe (1988, 1992) pointed out, the purpose of using a quadratic regression is to determine the fund's exposures to changes in the returns of major asset classes. This result is what is called a style analysis. Thus, the best set of asset class exposures sums to 100% and is nonnegative. In addition, this style analysis conforms with the rudimentary information in the fund's investment policy (assumes no net short positions in any asset class).

We compare this model to the regression model stated in Equation (2) without restriction to determine whether it yields similar results and, thus, whether it is a reasonable model for examining the correspondence between sensitivities and a manager's portfolio choices. The goal of this return-based style analysis is to find the "best" set of asset class exposures $\boldsymbol{\varphi_1}, \boldsymbol{\varphi_2}, \dots \boldsymbol{\varphi_J}$ that sums to 1 and conforms with the rudimentary information on the fund's policies. The best such set of exposures is the one for which the variance of $\widetilde{\varepsilon}_{i,t,}$—referred to as fund's tracking error over the style benchmark—is the least. As shown by Sharpe (1992), this method is not designed to find a style that "makes the fund look bad" (or good). Rather, the goal is to infer as much as possible about the fund's exposures to variations in the asset class returns during the period studied.

Also important is understanding that the "*style*" identified in such an analysis represents an average of the potentially changing styles during the period covered. Month-to-month deviations in the fund's return from that of the style itself can arise from the selection of specific securities within one or more asset classes, rotate among asset classes, or both. The term *selection* covers all such sources of tracking differences (Sharpe, 1992; Arik and Jagannathan, 2002).

5.2.2. Analysis of the multifactor model

As stated by Sharpe (1992), the usefulness of an asset class factor model depends on the asset classes chosen for its implementation. Although not strictly necessary, desirable asset classes should 1) be mutually exclusive, 2) be exhaustive, and 3) have returns with either low correlations with one another or different standard deviations in cases with high correlations.

Factor models are typically evaluated for their ability to explain the returns of the assets in question (i.e., the $\boldsymbol{R_{i,t}}$). A useful metric is $\boldsymbol{R^2}$ or the proportion of variance explained by the selected style benchmark asset classes. Using the traditional definition of R-square ($\boldsymbol{R^2}$), we have the following for asset or portfolio *i*:

$$\boldsymbol{R^2 = 1 - \frac{Var(\tilde{\varepsilon}_i)}{Var\,(\tilde{R}_i)}} \tag{6}$$

The right side of Equation (6) equals 1 minus the proportion of the variance that is unexplained. Thus, the resulting R-squared value indicates the proportion of the variance of $\boldsymbol{R_i}$ explained by the *n* asset classes.

Important to recognize is that this measure indicates only the extent to which a specific model fits the data at hand. A better test of the usefulness of any implementation is its ability to explain performance out of sample (Sharpe, 1992). Note that when quadratic programming is employed, because of the constraints ($\boldsymbol{0 \leq \varphi_{j,i} \leq 100}\%$ for each asset or portfolio *i*), the assumptions that lie behind such tests are violated, making true out-of-sample tests the only reliable means for evaluating the efficacy of the approach (Sharpe, 1992; Arik and Jagannathan, 2002).

The R-squared ($\boldsymbol{R^2}$) value is also a regular metric for identifying active from passive managers. The natural distinction between active and passive managers is provided by the decomposition of a managed portfolio return into two components: *style* and *selection*. A passive fund manager provides an investor with an investment *style*, whereas an active manager provides both *style* and *selection* (Sharpe, 1992).

An active manager looks for ways to improve performance by investing in asset classes and individual securities within each asset class that the manager considers underpriced. Therefore, the active manager deviates from the style of the performance benchmark index and selects individual securities within each style benchmark asset class that she considers to be a good buy. That is, the manager tilts toward style benchmarks undervalued and away from style benchmarks overvalued. In this sense, the active manager typically has different exposures to the style benchmark asset classes when compared with her performance benchmark. The manager also holds a different portfolio of securities within each style benchmark asset class and may also hold securities that fall outside the range of asset classes spanned by the style benchmarks. As a result, the benchmarks have lower explanatory power, and the residual terms $\widetilde{\varepsilon}_{\boldsymbol{i}}$ in Equation (2) is larger for managed funds relative to their respective performance benchmarks.

In contrast, passively managed funds do not buy and sell securities based on research and analysis; instead, the investment fund's assets are simply deployed among different asset classes. As a result, $\widetilde{\varepsilon}_{\boldsymbol{i}}$ is closer to zero for passively managed funds when compared with actively managed funds. In this sense, a passive fund manager provides an investor with an investment style, whereas an active manager provides both style and selection (Arik and Jagannathan, 2002).

5.2.3. Style benchmark return estimation

The effective asset mix represents the style of the investment fund's overall portfolio. Once the resultant styles have been estimated, that is, the "best" set of nonnegative style-asset class exposures $\boldsymbol{\varphi_1}, \boldsymbol{\varphi_2}, \ldots \boldsymbol{\varphi_J}$ that sum to 1 and minimize the variance of $\widetilde{\varepsilon}_{\mathbf{i,t}}$, the objective is now to estimate the benchmark return on the resultant style asset classes, that is, to estimate the times series of returns on the projected passive strategies or style benchmarks.

As shown by Sharpe (1992), a return-based style analysis provides a natural method for constructing benchmarks because the benchmark obtained is the result of the returns on a mix of asset classes with the same estimated style, where the style is estimated prior to the month in question. The benchmark selected as a performance measurement should be i) a viable alternative, ii) not easily beaten, iii) low cost, and iv) identifiable (Sharpe, 1988, 1992).

Once the style of the individual mutual funds has been estimated, we construct for each fund customized benchmark returns using the corresponding effective asset mix determined in Equation (5). The benchmark return for fund *i* is constructed as follows:

$$\boldsymbol{S_{i,t}} = [\boldsymbol{\varphi_{1,\mathrm{i}}} \times \boldsymbol{x_{1,t}}] + [\boldsymbol{\varphi_{2,\mathrm{i}}} \times \boldsymbol{x_{2,t}}] + \cdots [\boldsymbol{\varphi_{J,i}} \times \boldsymbol{x_{\mathrm{J},t}}] \quad (7)$$

where $\boldsymbol{S_{i,t}}$ are the returns on the styles benchmark for fund *i* in month *t*, that is, the benchmark return representing the style of the investment fund's overall portfolio for fund *j*; $\boldsymbol{\varphi_j}$ is the proportion of the "best" set of nonnegative style asset class exposures allocated to manager *j*, as obtained in Equation (5), that sum to 1; and $\boldsymbol{x_{n,t}}$ is the return on the benchmark index portfolio in month *t.* The terms in brackets are the portfolio benchmark returns that can be attributable by their exposure to the different style benchmarks, that is, the return on the resultant style calculated for month *t.*

Because the time series in the sample are rather short, we use a one-time period (the available months in the sample periods) to estimate the parameters used in the style benchmark.

The return obtained by a fund in each month can be compared with the benchmark return on a mix of asset classes with the same estimated style. The difference between the fund's return in month *t* and that of the style benchmark determined in Equations (2) and (7) is computed. This difference is defined as the fund's Estimated Selection Return for month *t*.

5.2.4. Assigning funds to categories – clustering

In this section, we explore an alternative classification method by grouping funds into clusters denominated by categories (or objectives) using the estimated benchmarks. We then compare this classification with the initial classification based on the descriptions in the funds' prospectuses or technical reports.

More specifically, once the estimated style benchmark via a constrained optimization procedure has been performed (Equation (5)) and the benchmark return on the resultant style has been calculated (Equation (7)), we cluster the time-series benchmark returns following the approach employed by Brown et al. (1997). Under this approach, we intend to determine whether funds can be classified into different categories or clusters that are more meaningful than the categories so far employed by the Colombian regulator or the categories inferred by reading the prospectuses or technical reports, which can be misleading or too generic.

If 1,2,…,*K* categories exist, the ex post total return in period *t* for any fund *i* can be represented as follows. Rearranging Equation (7) into Equation (2) yields the following:

$$\boldsymbol{R_{i,t} = \mu_{k,t} + \varepsilon_{i,t}} \tag{8}$$

where fund *i* belongs to style *k*. Thus, $\boldsymbol{\mu_{k,t}}$ is the expected return for category *k.* If the idiosyncratic return component $\boldsymbol{\varepsilon_{i,t}}$ has a zero mean ex ante and is uncorrelated across securities, the classification into categories suffices in explaining the cross-sectional dispersion of fund returns to the extent that $\boldsymbol{\mu_{i,t}}$ differs across styles (see Brown and Goetzman, 1977).

An exact solution to the style classification problem is only obtained through exhaustive combinatorics.

The method we use follows the approach employed by Brown et al. (1997), which is intended to find a local optimum via the minimization of a “within-group sum-of-squares” criterion during a specific period, $\boldsymbol{t = 1, \dots, T}$. The inputs procedure is a T-by-N matrix of benchmark returns for a set of N investment funds. We grouped the N funds into K styles by minimizing the within-style mean returns for each period $t = 1, \dots, T$. Thus, we jointly estimate the time series of the benchmark mean returns $\mu_{k,t}$ for the categories $k = 1, \dots, K$ for $t = 1, \dots, T$, and the membership to each style. As stated by Brown et al. (1997), the benefit of the resulting classification is that groups could result from either fixed portfolio strategies, such as similar asset composition, or dynamic portfolio strategies.

This procedure makes minimal demands on the available data because we only need to know the realized returns of individual funds. As Brown et al. (1997) pointed out, this estimation technique is a direct analogy with a cluster analysis procedure because the criterion applied is the same used in the k-means clustering approach. Cluster analysis usually attempts to minimize the squared differences within groups of *K* characteristics. In this context, the characteristics might include risk exposure and features of the average securities in the investment funds.

The classification procedures previously described assume that we know the number of categories. However, to determine the correct number of styles, we employed the algorithm described by Brown and Goetzman (1977) called the generalized least square procedure, which allows time-varying and fund-specific residual return variance. We also employed a likelihood ratio test suggested by Quandt (1960) for each successive decrease in the number of fund aggregations. Appendix 5 includes in detail the algorithm employed as an iterative relocation of a k-means, and Appendix 6 includes the Stata code used to implement this iterative relocation algorithm.

5.3. Empirical results

To identify styles and customize benchmarks from different style classifications, we analyze the realized investment fund returns from 2009 to 2015.

The model we use has eight asset classes (indices) from the sixteen indices analyzed (see Appendix 3 for the definitions of the indices and Table 10 for their correlations). We do not include in our analysis the indices coltescp, colteslp, dtfindex, coleqtyindex, colscindex, and colirindex because, as explained in the chapter on the data and main variables, these indices present high correlations among coltes, colibr, and colcap, respectively. Thus, we eliminate from the model those indices to avoid introducing systematic errors into the regression models. In addition, we eliminated from our model acwiindex and trmindex because those indices reference investments carry out abroad.

The return on each index represents the returns on a large number of securities. For reasons that will become clear, it is important to bear in mind that each index represents a strategy that could be followed at a low cost using an index fund (Sharpe, 1992).

The indices we use for the associated return series are as follows: Colombian treasury bills for the short and long term (COLTES and COLTES UVR); indices for fixed income securities in Colombia (COLIBR, TCC); inflation index rate in Colombia (COCPI); bond index of all types of fixed income instruments, including sovereign bonds, investment grade corporate bonds, and high yield bonds across developed and emerging markets (LEGATRUU); equity index in the Colombian stock market (COLCAP); and real estate asset index in the Colombian market (PEI).

5.3.1. Calculating funds exposures and styles – unconstrained regressions

Panel A in Table 11 provides an example of individual investment funds, in this case, six randomly selected investment funds (Fiducolombia Trust's funds, Fidubogota Trust's funds, Alianza Trust's funds, HSBC Trust's funds, and Colseguors Trust's funds). Columns 2 through 6 in Panel B of Table 11 provide the load's mean of all investment fund portfolios managed by trust companies in the Colombian market and employ the multifactor model in (1). Columns 2 through 6 in Panel C of Table 11 provide the summary statistics of robust standard errors and the t values of all investment fund portfolios managed by trust companies in the Colombian market and employ the multifactor model in (1). Monthly returns from June 2009 through December 2015 are used for the dependent variable, with the corresponding returns for the eight asset classes as independent variables.

Table 11: Summary statistics - Regression and Quadratic Programming Results for all Sample Funds Portfolio June 2009 through December 2015

Panel A: Unconstrained Regression and Quadratic Programming Results for Six Funds, randomly selected. From June 2009 through December 2015.

Asset Class	Unconstrained Regression						Quadratic Regression - Constrained					
	Fiducolombia Trust - Fund 3644	Fiducolombia Trust - Fund 3794	Fidubogota Trust - Fund 10660	Alianza Trust - Fund 11151	HSBC Trust - Fund 19466	Colseguros Trust - Fund 26433	Fiducolombia Trust - Fund 3644	Fiducolombia Trust - Fund 3794	Fidubogota Trust - Fund 10660	Alianza Trust - Fund 11151	HSBC Trust - Fund 19466	Colseguros Trust - Fund 26433
Coltes (T-Bills)	-0.083	0.616	0.013	0.000	0.064	-0.002	0.000	0.615	0.013	0.004	0.000	0.000
Coltes UVR - Mortgage	0.022	-0.004	0.022	0.009	-0.303	0.021	0.000	0.000	0.019	0.006	0.000	0.019
Cocpi - Inflation index	0.762	-0.200	-0.021	-0.019	-0.494	-0.005	0.041	0.000	0.000	0.000	0.000	0.019
Legatruu	0.106	0.027	-0.005	-0.001	0.343	-0.004	0.024	0.029	0.000	0.000	0.158	0.000
Col - IBR (Money Market)	1.890	-0.024	0.938	0.833	5.165	1.019	0.000	0.000	0.876	0.698	0.000	0.962
Colcap - Stocks	0.824	0.009	0.002	0.002	0.851	-0.001	0.808	0.010	0.002	0.003	0.842	0.000
Real Estate Index - PEI	0.191	-0.016	-0.003	0.002	-0.129	-0.010	0.128	0.000	0.000	0.002	0.000	0.000
TCC - Index Money Market	-1.691	0.274	0.144	0.382	-2.709	-0.208	0.000	0.345	0.090	0.288	0.000	0.000
Total	2.022	0.681	1.089	1.208	2.787	0.810	1.000	1.000	1.000	1.000	1.000	1.000
R-squared	93.71	88.25	56.22	74.27	94.83	43.68	93.17	88.03	55.42	71.90	93.31	41.12
R-squared Adj	93.01	86.87	51.35	70.90	93.80	30.03	92.91	87.54	53.07	69.70	93.16	38.10

Panel B: Mean Summary statistics – Unconstrained Regression and Quadratic Programming Results for all Sample Funds Portfolio June 2009 through December 2015

Asset Class	Unconstrained Regression						Quadratic Regression - Constrained					
	Average	Min	p25	p50	p75	Max	Average	Min	p25	p50	p75	Max
Coltes (T-Bills)	0.023	-0.355	0.001	0.015	0.031	0.616	0.029	0.000	0.000	0.012	0.023	0.615
Coltes UVR - Mortgage	0.002	-0.596	-0.003	0.015	0.032	0.411	0.021	0.000	0.000	0.009	0.027	0.325
Cocpi - Inflation index	0.037	-1.841	-0.061	-0.024	0.009	2.774	0.051	0.000	0.000	0.000	0.012	0.908
Legatruu	0.027	-0.737	-0.010	-0.004	0.007	0.955	0.019	0.000	0.000	0.000	0.002	0.322
Col - IBR (Money Market)	0.798	-5.000	0.298	0.605	0.891	14.280	0.508	0.000	0.107	0.620	0.753	1.000
Colcap - Stocks	0.081	-0.085	0.000	0.002	0.008	0.987	0.081	0.000	0.000	0.002	0.005	0.981
Real Estate Index - PEI	-0.009	-0.507	-0.011	-0.004	0.002	0.284	0.009	0.000	0.000	0.000	0.004	0.172
TCC - Index Money Market	-0.110	-12.480	-0.107	0.215	0.387	10.142	0.280	0.000	0.003	0.242	0.378	0.978
Total	0.848						1.000					
b_const	0.023	-0.355	0.001	0.015	0.031	0.616	-0.022	-2.013	-0.071	-0.031	0.021	0.973
R-squared	49.33	8.27	34.82	51.90	62.15	98.30	41.84	-20.86	22.38	48.24	56.86	97.85
R-squared Adj	40.04	-11.02	22.59	46.55	55.56	98.04	37.95	-28.58	15.48	44.17	55.13	97.81

Panel C: Standard errors (robust) and t-value - Unconstrained Regression and Quadratic Programming Results for all Sample Funds Portfolio June 2009 through December 2015

Standard Errors (Robust)

Asset Class	Unconstrained Regression						Quadratic Regression - Constrained					
	Average	Min	p25	p50	p75	Max	Average	Min	p25	p50	p75	Max
se_Constant	0.417	0.023	0.058	0.091	0.373	8.057	0.060	0.005	0.012	0.017	0.056	0.669
se_Coltes (T-Bills)	0.054	0.004	0.008	0.013	0.040	0.590	0.015	0.000	0.000	0.008	0.012	0.220
se_Coltes UVR - Mortgage	0.063	0.005	0.010	0.016	0.050	0.725	0.019	0.000	0.000	0.011	0.018	0.288
se_Cocpi - Inflation index	0.239	0.020	0.038	0.059	0.181	3.072	0.042	0.000	0.000	0.000	0.038	0.873
se_Legatruu	0.054	0.004	0.008	0.013	0.046	0.793	0.020	0.000	0.000	0.000	0.008	0.550
se_Col - IBR (Money Market)	1.018	0.086	0.165	0.276	0.842	16.211	0.129	0.000	0.021	0.111	0.160	0.770
se_Colcap - Stocks	0.015	0.001	0.003	0.004	0.012	0.186	0.011	0.000	0.000	0.002	0.006	0.122
se_Real Estate Index - PEI	0.044	0.004	0.007	0.011	0.036	0.618	0.010	0.000	0.000	0.000	0.007	0.202
se_TCC - Index Money Market	1.060	0.083	0.159	0.270	0.989	19.845	0.130	0.000	0.015	0.108	0.152	0.868

t_Value

Asset Class	Unconstrained Regression							Quadratic Regression - Constrained						
	Average	Min	p25	p50	p75	Max	Percentage of coefficients - Significance level at 5%	Average	Min	p25	p50	p75	Max	Percentage of coefficients - Significance level at 5%
t_Constant	0.428	-3.104	-0.889	0.067	1.340	8.793	21.31	-0.419	-14.691	-3.793	-1.556	1.141	26.291	62.84
t_Coltes (T-Bills)	1.406	-2.341	0.030	1.345	2.218	15.779	32.79	2.206	0.083	1.207	2.041	2.513	8.920	51.69
t_Coltes UVR - Mortgage	0.960	-2.644	-0.132	0.974	2.188	4.041	29.51	1.340	0.064	0.677	1.210	1.668	4.838	18.33
t_Cocpi - Inflation index	-0.398	-3.143	-1.021	-0.508	0.167	3.113	6.56	1.541	0.014	0.269	0.661	1.325	25.904	12.70
t_Legatruu	-0.253	-3.916	-1.077	-0.361	0.376	4.983	12.57	1.013	0.113	0.338	0.587	1.374	5.705	14.00
t_Col - IBR (Money Market)	2.357	-2.769	0.576	2.292	4.528	8.862	56.83	6.970	0.075	2.998	5.411	7.176	67.159	81.56
t_Colcap - Stocks	2.297	-1.835	0.021	0.700	1.499	46.602	15.30	2.950	0.016	0.704	1.140	1.877	28.945	23.39
t_Real Estate Index - PEI	-0.248	-2.723	-0.814	-0.363	0.263	2.649	4.37	0.938	0.041	0.409	0.740	1.259	3.501	9.68
t_TCC - Index Money Market	0.739	-3.424	-0.209	0.956	1.737	4.285	18.58	5.004	0.010	1.187	2.188	3.315	67.317	57.97

This Table in Panel A provides as an example the behavior of a manager's average exposures to asset classes over our sample for six individual investment funds, randomly selected, to provide a more representative view of the efficacy of the procedure. Columns 2 to 7 provides the unconstrained regression and columns 8 to 13 provides the quadratic programming results for these six individual investment funds´ Portfolio: Fiducolombia Trust´s funds, Fidubogota Trust´s funds, Alianza Trust´s funds, HSBC Trust´s funds and Colseguros Trust´s funds. Panel B columns 2 through 7 provides the summary statistics of all investment funds´ Portfolio managed by Trust Companies in the Colombian market, employing the multifactor model in equation (1). Panel C provides the robust standard errors and t-values for the lineal and quadradic regressions. In column 14 of the table t-values, from the quadratic regression from each independent investment funds we observe that 62.8% of the intercepts are significant at a level of 5%. This can be against of our predictive model, where it is supposed that the intercept should not have a level of significance different than zero. However, when we observe the significance level at 5% of the positive coefficients arisen from the quadratic regression, we realize that coefficient Col-IBR (Money Market) is significant for 82% of the investment funds, the coefficient TCC-Index Money Market is significant for 58% of the investment funds, the coefficient Coltes (T-Bills) is significant for 52% approximately of the investment funds, and the coefficient Colcap (equity stocks) is significant for 23% approximately of the investment funds. The rest of the coefficients are also significant at a level of 5% but in a much less proportion of the aforementioned coefficients. In our interpretation, this model captures the closest proxy to the fund´s passive investment strategy during the period 2009 to 2015. This model allows us for separate effects from each of the underlying asset classes and so might provide a more accurate customized style benchmark (Chan et al, 2002), which will be analyzed in the following sections. Monthly returns from June 2009 through December 2015 are used for the dependent variable, with the corresponding returns for the eight asset classes as independent variables. The column named “Unconstrained Regression” both in Panel A and

C show results obtained from applying equation (1). In Panel A, the first 7 rows show the resulting coefficients ($\boldsymbol{\beta}_{i,n}$) for the individual selected investment funds. In Panel B the first 7 rows show the summary statistics of the resulting coefficients beta ($\boldsymbol{\beta}_{i,n}$) for all investment funds from the sample period. As stated in equation (1), the coefficients do not sum to 1 and they are often negative. The last 6 columns in Panel A and B reports the results of applying the equation (5) subject to the restriction in equation (3) and (4) ("Quadratic Regression – Constrained"). For this analysis and considering the presence of inequality constraints, each coefficient needs to be positive and the sum is required to be 1. This requires the use of quadratic programming algorithm. This method reflects the fund´s actual investment policy (e.g. (Sharpe, 1992).

The "Unconstrained Regression" columns in Panels A, B, and C of Table 11 provide the results obtained from applying Equation (1). In Panel A, the first eight rows indicate the resulting coefficients ($\boldsymbol{\beta}_{i,n}$) for the selected investment funds. The total coefficient is shown in the next row, and then the R-squared is expressed in percentage form. From the example funds in Panel A, a substantial portion (from 43% to 95%) of the monthly variance in the fund's return is explained by this multifactor model. As stated in Equation (1), the coefficients do not sum to 1 (or 100%), and they are often negative. In Panel B, the first eight rows provide the summary statistics of the resulting coefficients' beta ($\boldsymbol{\beta}_{i,n}$) for all investment funds from the sample period. As Sharpe (1992) pointed out, these coefficients are inconsistent with the fund's investment policy (to invest in common securities with no short position).

5.3.2. Calculating funds exposures and styles – constrained regressions

The last six columns in Panels A, B, and C of Table 11 report the results of applying Equation (5) subject to the restriction in Equations (3) and (4) ("Quadratic Regression – Constrained"). For this analysis and considering the presence of inequality constraints, each coefficient needs to be positive, and the sum must be 1 (100%), requiring the use of a quadratic programming algorithm. As explained, the objective of the analysis ("Quadratic Regression – Constrained") is to select a set of coefficients that minimizes the unexplained variations in returns ($\widetilde{\varepsilon}_{t,p}$) subject to the described constraints.

These coefficients are positive and their total—shown in the next row—sums to 1 (or 100%). This method reflects the fund's actual investment policy (e.g., Sharpe (1992)). The addition of constraints causes a slight reduction in the R-squared value of the model compared with a linear regression.

Examining the behavior of a manager's average exposures to asset classes over our sample is helpful for some individual investment funds to provide a more representative view of the efficacy of the procedure. Thus, Panel A of Table 11 provides the results for six particular investment funds, randomly selected.

The "3794" and "11151" funds in Panel A of Table 11 decrease the R-squared from 88.25% to 88.03% (unconstrained and constrained regressions) and from 74.27% to 71.90%, respectively. However, because these coefficients reflect more closely the fund's investment style, they can be interpreted as portfolio weights. Thus, the model yields a (passive) mix of indices that minimizes tracking error volatility.

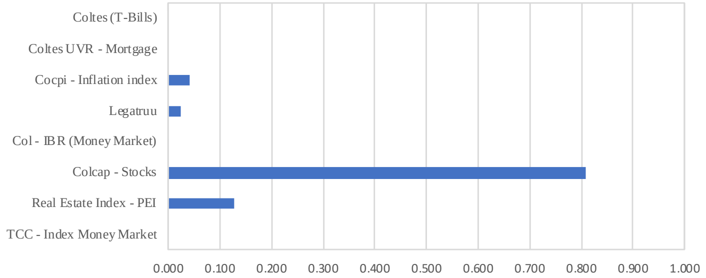
With the selected investment funds provided in Panel A of Table 11, the analysis suggests that the "3644" fund invests to obtain returns similar to those achievable with a portfolio with approximately 81% invested in the most liquid stocks in the market (colcap), 13% in real estate assets, and the remaining 6% in others securities to balance the portfolio. The second fund, 3794 for instance, invested approximately 61.5% in Colombian government bonds (T-bills) and 34.5% in money market assets. The analysis of the other funds ("10660," "11151," “19466,” “26433”) is carried out similarly. During the period investigated, for instance, the “3644” and “3794” funds, 93% and 88%, respectively, of the month-to-month variation in the fund returns could be explained by the concurrent variation in the return on this particular mix of asset classes.

The results for these six particular investment funds in Panel A of Table 11 columns (“Quadratic Regression – Constrained”) are represented graphically in Figures 7 through 12. The bar chart indicates the estimated style of the funds that represent the best set of asset class exposures, and the pie chart represents the associated R-squared value. As stated in the previous paragraphs, the R-squared ($\boldsymbol{R^2}$) is a regular metric[27] for decomposing a managed portfolio return into two components: *style* and *selection*. The R-squared value is attributable to the fund’s style and the remainder (1 – R-squared) to selection. A passive fund manager provides an investor with an investment style, whereas an active manager provides both style and selection (e.g., Sharpe (1992)).

Figure 7: Fiducolombia Trust - Fund 3644, June 2009 - December 2015, and Style based on monthly returns for all sample period

[27] In quadratic or constrained regression, the R-squared metric has its limitations as a measure of power in explaining the monthly variation in returns; see, for example, Knautz and Wilde (1993). These authors demonstrated that the R-squared metric in a restricted linear model is no longer useful if the restrictions are inhomogeneous—as in our case—because our analysis considers the presence of inequality constraints, for which each coefficient needs to be positive and the sum must be 1. They proposed a modification to the R-squared metric that captures all of the properties in the restricted model. In our study, we did not employ this R-squared proposed by Knautz and Wilde (1993) but used the regular R-squared metric. Thus, and given the presence of inequality constraints in our study, obtaining a negative R-squared to explain the monthly variation in returns is possible but does not mean that the technique is inadequate.

Figure 7
Fiducolombia Trust - Fund 3644
June 2009 - December 2015



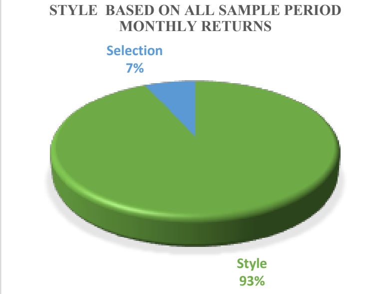
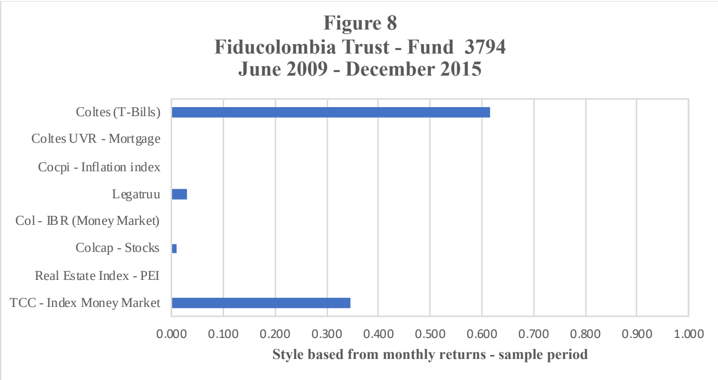


Figure 8: Fiducolombia Trust - Fund 3794, June 2009 - December 2015, and Style based on monthly returns for all sample period



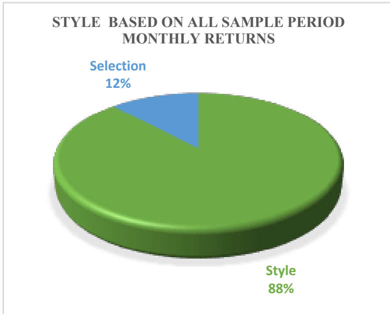
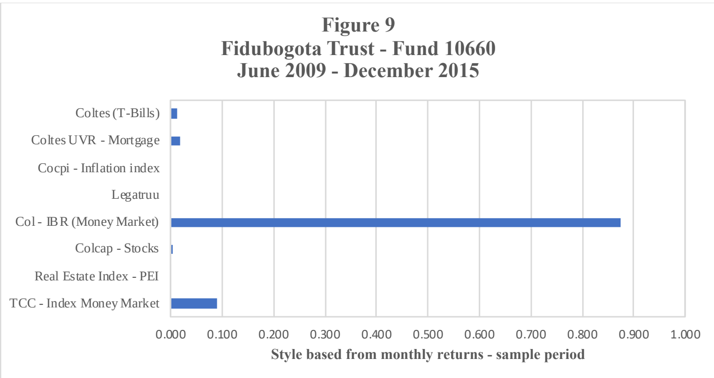


Figure 9: Fidubogota Trust - Fund 10660, June 2009 - December 2015, and Style based on monthly returns for all sample period



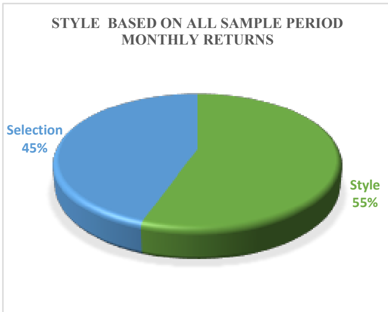
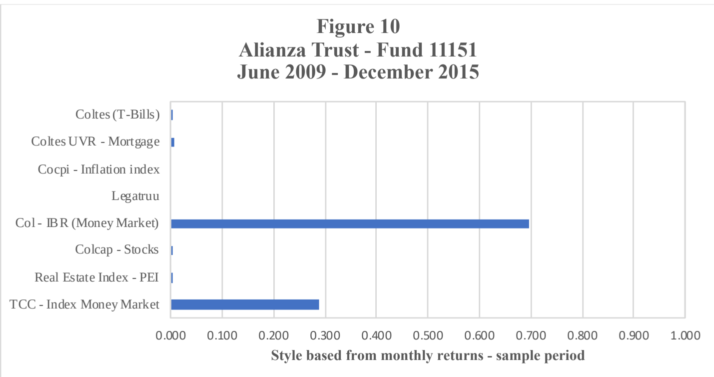


Figure 10: Alianza Trust - Fund 11151, June 2009 - December 2015, and Style based on monthly returns for all sample period



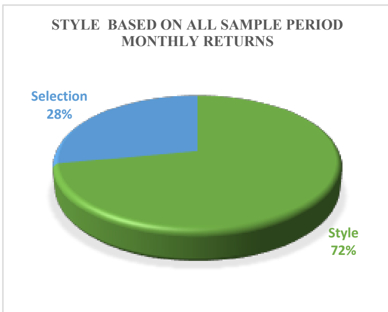
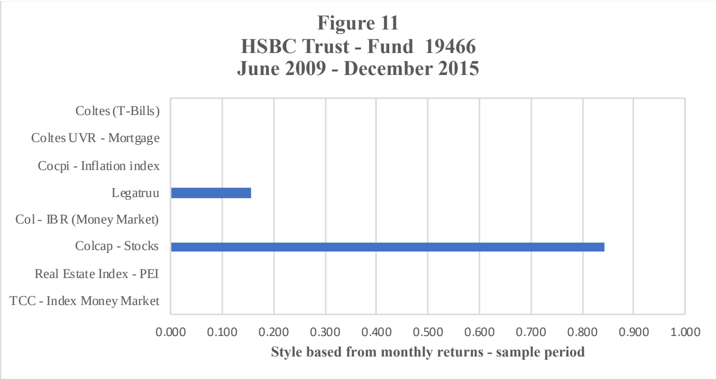


Figure 11: HSBC Trust – Fund 19466, June 2009 - December 2015, and Style based on monthly returns for all sample period



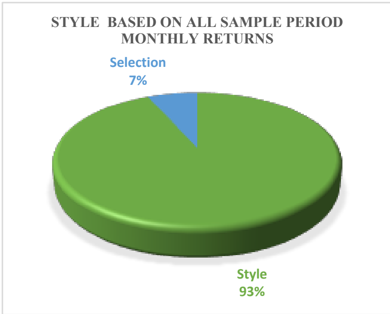
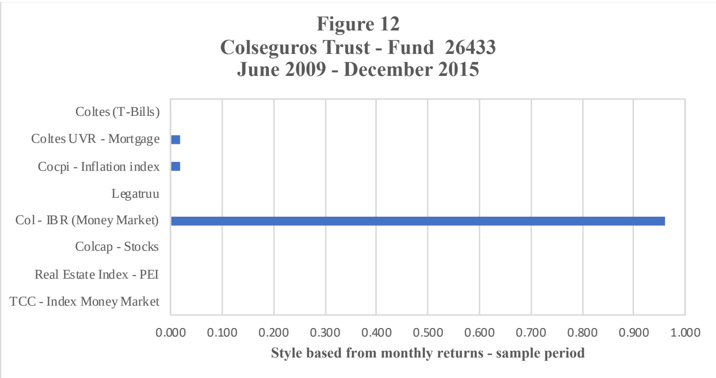
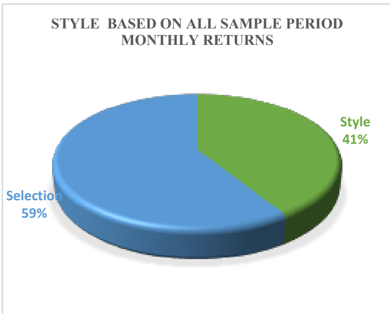


Figure 12: Colseguros Trust - Fund 26433, June 2009 - December 2015, and Style based on monthly returns for all sample period





Figures 7 through 12 provide the results obtained by applying this type of analysis for these six particular investment funds. As Figure 7 indicates, its style differed considerably from that of the funds represented in Figures 8, 9, 10, and 12, and similar to the fund represented in Figure 11. The funds in Figures 7 and 11 emphasize more liquid stocks than the other funds. Figure 8 indicates that the fund is considerably more focused on Government bonds (Coltes – T-bills) and money market assets (TCC Index). The fund represented in Figure 9 has highly concentrated exposure to money market assets (IBR Index). Figure 10 shows that the fund is also highly concentrated in money market assets but diversified in IBR and TCC indices. Figure 11 shows that its exposure is highly concentrated in stocks and a small proportion in corporate debt. In addition, Figure 12 shows that the fund is considerably more diversified, having in its portfolio a large proportion of money market assets but also Government bonds (Coltes UVR) and local debt tied to inflation.

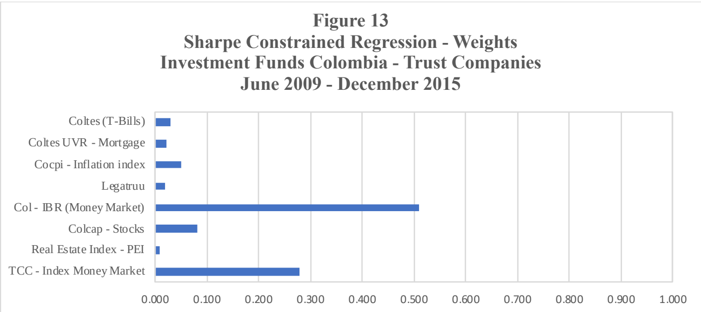
It is important to bear in mind that the style identified for these six particular investment funds (shown in Figures 7 through 12) in such an analysis (R-squared) is an average of potentially changing styles from June 2009 to December 2015. As Sharpe (1992) pointed out, month-to-month deviations in the fund's return from that of the style can arise from the selection of specific securities within one or more asset classes, rotation among asset classes, or both security selection and asset class rotation. In this analysis, the term selection is employed to cover all such sources of tracking differences.

The R-squared value might be viewed as a sole indicator of active management. However, a higher R-squared value also implies that the technique is better and can often more consistently explain the long-term return behavior of the fund. As Ben Dor et al. (2002) pointed out in a style analysis, the use of an inadequate set of benchmarks might result in a low R-squared. Thus, drawing inferences on a fund solely from the overall power of the technique to explain the monthly variation in returns (R-squared) is improper without considering the potential style changes over time. In this sense, examining the behavior of a manager's average exposures to asset classes and performing a series of style analyses using a fixed number of months for each analysis through time (rolling month-by-month returns) are helpful. However, this condition is a limitation in our study because of the monthly time series data that we have for the investment funds—some funds do not allow us to perform a series of style analysis (rolling month-by-month returns) for periods longer than 48 months.

During this stage, we show the results for six particular investment funds. We now provide a more representative view of the efficacy of the Sharpe (1992) approach performed for each of 183 investment funds using returns from June 2009 through December 2015. In this analysis, we use the averages for both the styles and R-squared values of all funds.

The column "Quadratic Regression – Constrained" in Panel B of Table 11 provides the average of the resulting coefficients ($\boldsymbol{\varphi_{1,i}}$ values) for all investment funds, that is, the styles of all funds. Figure 13 represents graphically the average of the estimated style of all funds presented in Panel B of Table 11, "Quadratic Regression – Constrained" (bar chart), and the variance based on style (pie chart).

Figure 13: Investment Fund Style Analysis for All Investment Funds since June 2009 through December 2015, and Style based on monthly returns for all sample period



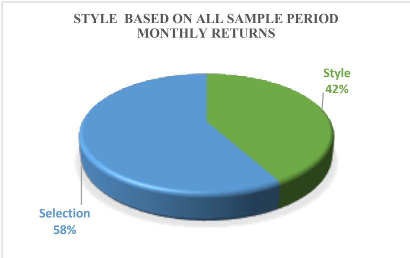


Figure 13 portrays an interesting result for the investment funds in the market. Here, the most prominent exposure is, as expected, money market assets that represent more than 79% in the movements of the returns of the IBR (50.8%) and TCC (28%) asset classes (see Panel B of Table 11, "Quadratic Regression – Constrained"). A small proportion of stocks (Colcap) (8.1%) reflects a lack of liquidity and development of the stock market in Colombia. Note that the exposure to Colombian Bills (5%) probably results from the actual holdings that many funds maintain to meet liquidity needs and reduce exposure to risk.

Columns 8 through 15 in Panel C of Table 11 provide the robust standard errors and t-values for the quadratic regressions. Column 15 of Panel C in Table 11 (t-values table) shows that, from the quadratic regression of each independent investment fund, 62.8% of the intercepts are significant at the 5% level. This finding contradicts our predictive model, for which the intercept should not have a significance level different from zero. However, when we observe the 5% significance level for the positive coefficients from the quadratic regression, we realize that the Col-IBR (Money Market) coefficient is significant for 82% of the investment funds, the TCC-Index Money Market coefficient is significant for 58% of the investment funds, the Coltes (T-bills) coefficient is significant for approximately 52% of the investment funds, and the Colcap (equity stocks) coefficient is significant for approximately 23% of the investment funds. The rest of the coefficients are significant at the 5% level but in a much lower proportion than the aforementioned coefficients. Our interpretation is that this model captures the closest proxy to the fund's passive investment strategy from 2009 to 2015.

On average, we find evidence that investment funds in Colombia respond significantly to movements in the returns of the following three asset classes (see Panel C of Table 11 – Quadratic Regression): Government bonds (Coltes – T-bills), money market assets (IBR Index), and cash assets (TCC Index). We also find evidence—although in a much lower proportion—that investment funds in Colombia respond significantly to movements in the returns of the other five asset classes: ColtesUVR, Cocpi, Legatruu, Colcap, and PEI (see Panel C of Table 11 – Quadratic Regression).

This style analysis procedure can detect some of the subtleties that exist in practice in the investment fund industry in Colombia, instead of classifying each fund by a single style. This result illustrates the fact that most of the funds, in essence, behave similarly to a passive portfolio invested in money market assets, which might also represent a lack of sophistication of the investment fund industry in Colombia. As a result, style accounts for a small part—on average, 42% (R^2 for the constrained regressions)—of the variance in the return.

In our results, the low R-squared value might be viewed as a sole indicator of low active management or, rather, might also be seen as an inadequate technique is because the indices of the major asset classes used are not complete or representative. Our results are consistent with both explanations. We support the first conclusion because we have included in our model the most representative and complete asset classes that exist in the Colombian market to explain the monthly variation in returns. Thus, the low R-squared value is an indicator of low active management. However, we might also support the alternative conclusion because we have not been able to examine the behavior of a manager's average exposure to asset classes, given the absence of a more sophisticated benchmark in our market and that some funds do not allow us to perform a series of style analysis over time (rolling month-by-month returns for periods longer than 48 months). In this case, this condition is a limitation of our study.

However, we believe that our model allows for separate effects from each of the underlying asset classes and, thus, might provide a more accurate customized style benchmark (Chan et al., 2002). In addition, as demonstrated by Sharpe (1992), this procedure shows a remarkable amount of information revealed from an analysis of the returns provided by the manager of an investment fund. This is especially important because, in the final analysis of returns, investors buy this product from such a manager.

5.3.3. Calculating customized benchmark return based on Sharpe implied portfolios weights

Thus, as part of method 2, once the style of all individual investment funds has been estimated in Equation (5), determining the corresponding benchmark return associated with the effective asset mix is quite straightforward. Given that our ultimate goal is to evaluate whether investors have enough information to evaluate fund performance in the Colombian market, we should customize benchmark returns to evaluate fund performance because the style fund classifications provided by the regulator actually do not help us provide useful benchmarks for these purposes.

Equation (7) suggests a procedure to construct for each fund's customized benchmark returns using the corresponding effective asset mix. Table 12 provides the summary statistics of the customized benchmark based on the Sharpe

(1992) implied portfolio weights for some selected investment funds and the average of the total investment funds managed by trust companies in the Colombian market.

Table 12: Summary Statistics of customized Benchmark Returns based on Sharpe (1992) implied portfolios weights for some selected investments funds and the average of the Customized Benchmark by all investment funds.

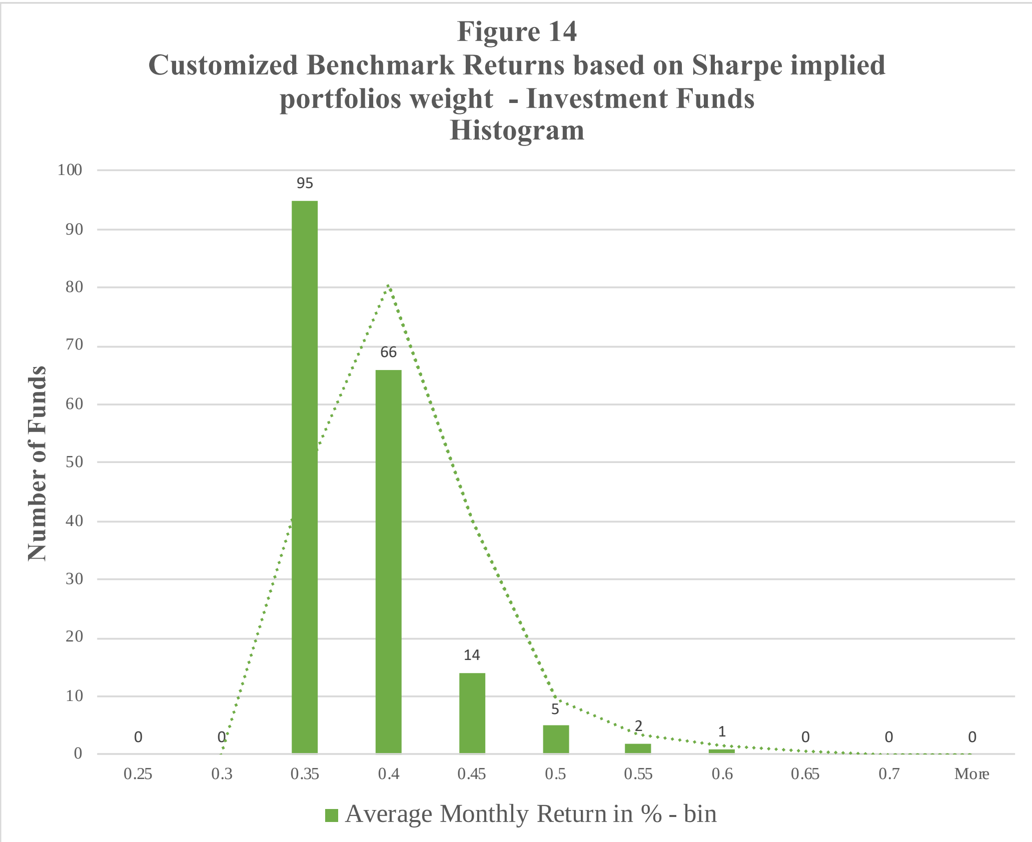
fund_code	N	mean	sd	min	p25	p50	p75	max
2276	84	0.508	3.145	-6.033	-1.704	0.366	2.626	8.065
2852	84	0.356	0.111	0.057	0.293	0.331	0.423	0.826
2971	84	0.357	0.127	0.047	0.273	0.350	0.428	0.803
2990	84	0.360	0.135	0.011	0.270	0.353	0.435	0.834
3010	84	0.366	0.145	-0.030	0.270	0.362	0.447	0.901
3019	84	0.360	0.135	0.011	0.269	0.352	0.436	0.833
3031	84	0.360	0.135	0.011	0.269	0.352	0.436	0.833
3040	84	0.361	0.135	0.006	0.273	0.362	0.434	0.842
3049	84	0.372	0.169	-0.145	0.254	0.371	0.461	0.957
3078	84	0.373	2.431	-4.422	-1.427	0.292	1.919	6.412
3644	84	0.439	3.658	-7.256	-2.092	0.049	3.026	9.047
3685	84	0.461	3.794	-7.610	-2.142	0.050	3.138	9.478
3721	84	0.341	0.108	0.148	0.266	0.324	0.395	0.718
3781	84	0.335	0.084	0.204	0.282	0.314	0.356	0.634
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
33187	84	0.380	3.160	-6.007	-1.874	0.174	2.437	8.031
33355	84	0.329	0.102	0.087	0.276	0.308	0.371	0.636
33640	84	0.356	0.185	-0.078	0.228	0.354	0.457	0.861
33642	84	0.346	0.133	0.060	0.257	0.329	0.413	0.755
33643	84	0.395	3.412	-6.485	-1.980	0.034	2.587	8.540
34166	84	0.324	0.146	-0.006	0.216	0.311	0.419	0.790
34908	84	0.338	0.090	0.121	0.284	0.326	0.383	0.611
36570	84	0.327	0.088	0.208	0.267	0.300	0.361	0.618
37238	84	0.333	0.096	0.100	0.279	0.318	0.375	0.633
37240	84	0.333	0.096	0.100	0.279	0.318	0.375	0.633
41248	84	0.352	0.100	0.111	0.288	0.342	0.405	0.814
51954	84	0.380	0.166	-0.191	0.279	0.365	0.459	1.079
51959	84	0.434	0.375	-0.860	0.221	0.451	0.638	1.519
Average	**84**	**0.361**	**0.489**	**-0.706**	**0.032**	**0.316**	**0.672**	**1.671**

This table presents the summary statistics of customized benchmark Returns based on Sharpe (1992) implied portfolios weights for some selected investments for some selected investment funds and the average of the total investment funds managed by Trust Companies in the Colombian market. *N* in the table refers to the number of observations from year 2009 to year 2015.

The customized benchmark returns on the resultant style are calculated for each month *t* for all investment funds during the sample period.

As observed in Table 12, the customized benchmark return using the corresponding asset mix for all investment funds investigated represents an average of 0.36% per month, with an average standard deviation of 0.48%. Figure 14 graphically represents that 161 investment funds (89% of the total investment funds investigated) have, on average, a benchmark return between 0.35% and 0.4% per month.

Figure 14: Histogram of Customized Benchmark Returns based on Sharpe implied portfolios weights - All Investment Funds



By using the corresponding asset mix to analyze the style benchmark returns based on the Sharpe (1992) implied portfolio weights, we customized the style benchmark return that can be applied directly to measure the manager's selection skill given a fund's alpha.

In the next section, we compare the return obtained by a fund in each month with that of a predetermined benchmark asset mix to evaluate the value added or lost from asset allocation decisions, that is, the alpha for each investment fund.

5.3.4. Category classification – cluster analysis

At this stage, we have taken the averages for the styles of all of the funds and have customized—based on these styles—the benchmark returns for evaluating fund performance. Now, we want to show the robustness of this approach in the style analysis to empirically classify each of the 183 investment funds using the customized benchmark returns from June 2009 through December 2015.

Given that i) the current classification provided by the regulator is useless for inferring anything about the strategies of advisory companies and ii) the classification of funds we have developed by extracting the investment policy from the prospectuses or technical reports (see Table 3) might involve substantial judgment, the objective of this method is to empirically classify the investment funds considering the style benchmark returns based on the Sharpe (1992) implied portfolio weights (method 3 previously described).

No generally accepted standards exist to objective classifications and very few exist for comparison purposes, which are put to a broad range of uses as

Brown et al. (1997) pointed out—from developing benchmarks for risks and returns to establishing specifications used in investment management contracts. The procedure we have employed follows the asset pricing literature.

Once the customized benchmark returns are computed, specifically, we first employed for these data the $\boldsymbol{SSQ_j}$ algorithm described in Equations (9) through (11) and the likelihood ratio (*LR*) in Equation (12) to determine the number of styles to be chosen (see Appendix 5 for description of these equations). Then, we cluster in the space of the Sharpe (1992) quadratic regression the customized benchmark returns to determine empirically the investment objective. We compare our empirically determined objectives with the classification made in this study based on their aggregation of individual securities extracted by technical reports to evaluate and observe how the investment funds that are empirically investigated behave considering the realized returns. We compare the empirically determined styles with the classification previously mentioned because no industry classification exists in the Colombian market that we might use, such as Morningstar.

5.3.4.1. Number of objectives

Applying Equations (11) and (12) to the customized benchmark returns, we find evidence for using at least five separate categories. As Brown et al. (1997) pointed out, some ambiguity exists about the appropriate degrees of freedom and the appropriateness of the $\boldsymbol{X^2}$ distribution in this case. However, for k = 5 through k = 3 styles, the test statistic values amount to 567.31, 842.85, and 462.76, respectively. In each case, the *p-values* are close to zero, indicating that an increase in the number of styles is useful for explaining returns. This result is similar to that reported for X^2 test for the number of factors, where typically too many factors are identified (see Brown and Goetzmann, 1997). Using fewer than six groups, the *p-values* suggest that the X^2 test is well specified. However, using a lower number of groups, the algorithm clearly forces disparate funds together, which increases the model error. When the number of groups is increased beyond *k>5*, the *p-values* are close to 1, indicating that an increase in the numbers of styles beyond five is not useful for explaining returns. Thus, the X^2 test is well specified for all values below six (*k<6*), suggesting that more groups are not needed.

5.3.4.2. Style classification categories

In Panels A and B of Table 13, we report the cross-tabulation of the style classification defined by the regulator (Panel A) and the style classification performed by reading the legal prospectuses and monthly reports (Panel B) with our empirically determined categories.

Because the classification made by the regulator is too broad, and the classification based on the investment portfolio of individual securities extracted by the technical reports is the result of our inference about the basic strategy described in each legal prospectus and monthly report, we do not expect a perfect correspondence with our empirical categories.

Table 13: Cross-tabulation of funds by Empirical Style Categories and Colombia´s SEC classification and Prospectus Classification, summary of results using style classification algorithm, June 2009 to December 2015

Panel A: Cross-tabulation of funds by Empirical Style Categories and classification made by the regulator (Colombia´s SEC), summary of results using style classification algorithm, June 2009 to December 2015

Classification made by the Colombia´s SEC	Empirical Style Categories					Total
	1	2	3	4	5	
Equity	1	0	0	0	0	1
General	14	121	21	7	3	166
Money Market	0	6	0	0	0	6
Real Estate	0	7	3	0	0	10
Speculative	0	0	0	0	0	0
Total	**15**	**134**	**24**	**7**	**3**	**183**

Panel B: Cross-tabulation of funds by Empirical Style Categories and classification based on the information extracted by the technical reports, summary of results using style classification algorithm, June 2009 to December 2015

Classification made by Prospectus	Empirical Style Categories					Total
	1	2	3	4	5	
Balanced	0	2	4	4	3	13
Debt	0	101	16	3	0	120
Equity	15	6	1	0	0	22
Money Market	0	17	0	0	0	17
Real Estate	0	8	3	0	0	11
Total	**15**	**134**	**24**	**7**	**3**	**183**

This table Panel A and Panel B report the cross-tabulation of the style classification made by the regulator and the classification performed by reading the legal prospectus and monthly reports, with our empirical determined categories. The empirical style category is the maximum likelihood method described in Appendix 5. A likelihood ratio suggested by Brown and Goetzmann (1997) shows that the cross-section of investment fund returns is driven by at least five *(k=5)* separate factors, for which loading may vary.

The important aspect of Panel B of Table 13 is that the Debt and Money Market categories, which are the single largest designations for the classification based on the prospectuses, are concentrated in only one empirical style classification, especially in Category 2. The same result is observed in Panel A of Table

13 because the General category, which is the largest classification made by the regulator, is concentrated in the same empirical style Category 2.

In addition, Panels A and B of Table 13 indicate that many other different portfolio strategies can fall under Category 2. For instance, we observe in Panel B of Table 13 that some of the investment funds classified in Equity, Balanced, and Real Estate fall in Category 2. Indeed, the empirical style classification algorithm groups a significant percentage of investment fund strategies of general, equity, money market, and real estate funds, suggesting that these local labels created by the regulator (Table 3 Panel A) do not provide particularly useful distinctions for investors. Additionally, General (Panel A) or Debt (Panel B) funds are spread in different empirical style classification categories as the most representative of Category 2; a significant percentage of Money Market funds (in Panels A and B) fall in category 2; Real Estate funds (in Panels A and B) are also spread in category 2, Equity funds are widely spread in Category 1, a significant percentage in category 2 and a small proportion in Category 3 (Panel B of Table 3). Apparently, General funds classified by the regulator (Panel A), Debt funds classified by the prospectus (Panel B), and Money Market funds and Real Estate funds fall in full under Category 2. Equity funds are classified in Categories 1, 2, and 3, and a significant percentage are in Category 1. Group 1 also appears to be composed mostly of equity funds; group 2 is composed mostly of general, debt, or money market funds; and the rest of the funds are spread among groups 3, 4, and 5, suggesting that investment funds in Colombia managed by trust companies are not widely diversified.

Given our empirical determined categories, the classification that investors may infer from reading the prospectuses or technical reports—or even the classification made by the regulators—is misleading in many cases, suggesting that an industry classification is absent in the Colombian market.

Table 14 provides further insights into the characteristics of the empirical style categories. For each category, we estimate the Sharpe (1992) portfolio weights' mean, standard deviation, median, and proportion of the coefficients that are significant at the 5% level, assuming the entire sample period (nonoverlapping) return. As described in the previous sections, following Sharpe (1992), we constrain the coefficient to be positive and sum to one to allow them to be interpreted as weights in short sale-constrained analog portfolios (see Brown and Goetzman, 1997). Group 1 has a large average exposure to the COLCAP stock index (80.6%) with 100% significance for this coefficient. Group 2 has a large average exposure to money market indices, such as IBR (61.7%) and TCC (33.4%), and IBR is significant in 78% of the cases, and TCC is significant in 53% of the cases. Group 3 is widely spread in exposures to IBR (40%), securities tight to inflation (24.4%), TCC (18.5%), and government bonds (COLTES and COLTES-UVR – 12.8%); however, the distribution of the significance level of these coefficients is more spread. Group 4 is widely spread in Colombian government bills (COLTES – 26.3%), exposure to securities tight to inflation (22%), COLCAP stocks (13.6%), and the TCC index (17.3%), where COLTES and COLCAP index have a significance level of 71.4%. Group 5 has a large exposure to the COLCAP stock index (41.6%) and is widely spread in exposure to the TCC index (27.6%) and debt securities (Legatruu – 22%), with 100% significance for the COLCAP coefficient and 33% significance for TCC and Legatruu.

Table 14: Mean, standard deviation, median, and the weight of the coefficients that are significant of all months (non-overlapping) Sharpe implied portfolios weights, benchmark customized returns

Emperical Classification	coltes	coltesuvr	cocpi_index	legatruu	colibr_index	colcap_index	pei_index	tcc_rate
1								
mean	0.023	0.001	0.015	0.132	0.006	0.806	0.017	-
sd	0.068	0.004	0.045	0.117	0.015	0.114	0.045	-
count	15	15	15	15	15	15	15	15
median	-	-	-	0.123	-	0.810	-	-
Significance level of coefficient (proportion)	-	-	-	0.333	-	1.000	-	-
2								
mean	0.014	0.013	0.013	0.003	0.617	0.002	0.004	0.334
sd	0.016	0.014	0.041	0.009	0.276	0.004	0.009	0.273
count	134	134	134	134	134	134	134	134
median	0.011	0.009	-	-	0.673	0.001	-	0.293
Significance level of coefficient (proportion)	0.343	0.090	0.022	0.007	0.784	0.030	0.030	0.537
3								
mean	0.057	0.071	0.244	0.010	0.400	0.011	0.023	0.185
sd	0.053	0.065	0.318	0.023	0.314	0.023	0.051	0.261
count	24	24	24	24	24	24	24	24
median	0.056	0.066	0.106	-	0.455	-	-	-
Significance level of coefficient (proportion)	0.375	0.333	0.208	-	0.375	0.042	0.083	0.125
4								
mean	0.263	0.052	0.220	0.036	0.094	0.136	0.026	0.173
sd	0.217	0.047	0.220	0.084	0.232	0.090	0.059	0.186
count	7	7	7	7	7	7	7	7
median	0.229	0.044	0.288	-	-	0.131	-	0.190
Significance level of coefficient (proportion)	0.714	-	-	-	0.143	0.714	-	0.286
5								
mean	-	-	-	0.219	0.023	0.416	0.066	0.276
sd	-	-	-	0.134	0.039	0.075	0.093	0.296
count	3	3	3	3	3	3	3	3
median	-	-	-	0.268	-	0.413	0.026	0.239
Significance level of coefficient (proportion)	-	-	-	0.333	-	1.000	-	0.333

This table reports summary statistics about the time-series of Sharpe´s (1992) portfolio weights, assuming the entire sample period (non-overlapping) return. We constrain the coefficient to be positive and sum to one, so that they can be interpreted as weights in short-sale constrained analogue portfolios (Brown and Goetzman, 1997). In addition, we report the proportion of the coefficients that at the level of 5% are significant.

Table 15 reports a cross-tabulation of all investment fund attributes with our empirical style classification groups, which reveals useful information about funds' group strategies. For instance, the average of the total asset value for category 1 is approximately half the size of category 2, even though category 2 represents more than two-thirds of the total number of investment funds investigated (see Table 13 for the number of funds per category). However, the average of the total family asset value for category 1 is more than twice the family size of category 2, and this category represents— as we mention—more than two-thirds of the total number of investment funds investigated. Something similar happens with Category 5: the average of the total family asset value for category 5 is approximately half the size of categories 2, 3, and 4, even though category 5 represents the lowest total number of investment funds investigated (see Table 13). The overall net money flow into our sample of funds is relatively small, and this feature remains the same for each empirical category; however, category 1 has a higher net money flow among the other categories. The effective fee rates are approximately 1.73% overall; however, category 1 has the highest effective fee rate (2.2%), which should be consistent with the risk taken if we assume that this category reflects the Equity strategy. Something interesting that we observe here is that, for category 1, 8.9% of the contractual incentives (*concave linear dummy*) might be classified as concave contracts, that is, incentives that change based on total assets, even though concave contracts are nonexistent, as we have described in the data and variables chapter. This observation is counterintuitive in some fashion because we expect that contractual incentives for category 1 (equity funds) should be more powerful and, thus, more linear than other categories—or at least as linear as other categories. This result for category 1 is also confirmed because the *Coles' incentive rate* variable takes the value of 0 for linear contracts and negative values for concave contracts, with the incentive increasing as this variable increases. The TER is approximately 2.1% overall, and category 1 has the highest TER rate (3.03%) at almost twice that for category 2, which can be assumed to be money market funds. The turnover across the categories is very small, but the differences are interesting. Category 2 has the highest estimated turnover—approximately 20% of its average asset value was purchased or sold over one year. The turnover in the rest of the categories is apparently nonexistent. The corresponding figures indicate that categories 1, 3, 4, and 5 are less active than category 2. Nonetheless, the effective fee rate for categories 1 and 5 are higher than for the rest of the categories, which is not consistent with trading activities. Of the last 12 months, Category 1 has the highest fund return volatility, at approximately 4.3%, and Category 2 has the lowest fund return volatility, at approximately 0.19%, followed by Categories 3, 4, and 5. These corresponding figures should be consistent with the risk taken if we assume that category 1 reflects the equity strategy, and category 2 reflects the money market strategy. In Panel B of Table 13, 101 funds are reported as debt funds and six are reported as equity funds, as per the classification in the prospectuses. However, according to our empirical style classification, such funds are assigned to Category 2, which—as is subsequently mentioned—corresponds to money market funds. The investment policies in the prospectuses show that we do not have evidence to conclude that fund managers intentionally classify these funds as debt or equity funds solely to charge higher commissions. However, we believe that classifying funds in a more accurate manner and reporting such public information generates transparency and legitimacy to the market and investors and allow them to make better decisions and obtain better returns.

Table 15: Average value of funds attributes by Empirical Style Categories

Variables	Empirical Style Categories				
	1	2	3	4	5
Effective fee rate (% annual)	2.200	1.651	1.888	1.640	2.231
Cole´s incentive rate	-0.071	0.000	0.000	0.000	0.000
Weighted incentive rate	0.973	1.000	1.000	1.000	1.000
Incentive ratio	1.000	1.000	1.000	1.000	1.000
Concave linear dummy	0.089	0.000	0.000	0.000	0.000
Performance based fee dummy	0.000	0.172	0.177	0.000	0.000
Front Load Fees dummy	0.000	0.042	0.063	0.000	0.000
Back Load Fees dummy	0.283	0.280	0.601	0.389	0.000
Fund return before fee (% monthly)	-0.270	0.349	0.299	0.339	0.213
Fund TA (COP Million)	164,331.30	304,743.88	86,921.49	48,452.45	50,486.85
Ln (Fund TA)	9.510	11.153	10.279	8.906	9.065
Family TA (COP$ Million)	5,543,996.00	2,210,630.62	2,236,671.94	2,523,872.19	4,213,329.66
Ln (Family TA)	15.115	13.769	13.656	14.038	14.751
Fund return volatility_30d	0.774	0.024	0.066	0.146	0.337
Fund return volatility_12m	4.293	0.189	0.577	1.198	1.885
Net money inflow (COP Million)	2,889.40	1,610.47	343.81	886.57	360.88
New Money Inflow (%)	0.064	0.056	0.105	0.077	0.010
Turnover	0.039	0.201	0.043	0.056	0.043
Open-end Closed-end Funds	1.000	0.945	0.855	1.000	1.000
Advisory Age (months)	299.084	267.924	307.558	303.544	399.070
Fund Age (months)	79.238	152.546	144.964	62.968	204.784
Ln (Fund Age)	4.22	4.77	4.76	4.01	5.30
Minimum required invesment (COP Million)	88.166	1037.611	324.687	0.962	0.772
Ln (Minimum Investment)	12.74	13.78	14.16	13.76	13.50
Average account size (COP Million)	410.670	1607.666	281.227	356.214	20.643
Ln (Account Size)	3.749	5.061	4.121	4.534	2.808
TER (% annual)	3.036	1.995	2.067	1.874	2.642
TER (% monthly)	0.247	0.164	0.169	0.155	0.217
Q/Max	0.540	0.564	0.574	0.396	0.333
Ln (Q/Max)	-0.756	-0.777	-0.806	-1.313	-1.558
Sub-Advisory Management Fund	0.108	0.000	0.000	0.000	0.000
Manager Postgraduate Certific dummy	0.645	0.633	0.668	0.781	0.231
Manager Master Education dummy	0.392	0.454	0.260	0.503	0.874
Manager gender	0.854	0.863	0.629	0.450	0.995
Tenure Manager (years)	9.618	11.021	11.679	9.503	11.407
Ln Tenure Manager (months)	4.680	4.795	4.846	4.684	4.855
Selection Return	-0.222	0.015	-0.056	-0.006	0.020
Alpha rolling estimation Sharpe	-0.220	0.009	-0.061	-0.031	-0.125
Alpha rolling estimation Prospectus	-0.247	-0.047	-0.154	-0.198	-0.224
Alpha rolling estimation Carhart	-1.502			-0.314	-1.095
Alpha single estimation Sharpe	-0.210	0.018	-0.042	-0.016	0.029
Alpha single estimation Prospectus	-0.238	-0.063	-0.160	-0.170	-0.091
Alpha single estimation Carhart	-0.899			-0.262	-0.516

This table reports cross-tabulation of all investment funds attributes with our empirical style classification groups

Although these data represent a snapshot of the funds as of the last date in our database, we believe that they provide important validation for the style classification procedure.

We take Tables 13 and 14 together to suggest a classification as the basis for performance and measurement compensation that can be useful for the regulator and investors and that should replace the classification provided by Colombia's SEC, given the limited information that exists in the local market. Tables 13 and 15 show that the classification by the regulator and that established from the data provided by the technical reports and prospectuses are incorrect. The following categories summarize our empirical style classifications:

Category 1: "*Equity – Growth*" is comprised primarily of liquid stocks for growth funds. This category represents investment funds that have the highest positive weights of any category in the COLCAP index. They invest in relatively the most liquid stocks listed on the Colombian stock exchange.

Category 2: "*Money Market*" is comprised primarily of money market funds. This category includes investment funds that have the highest positive weights regarding COLIBR and the TCC rate. These funds invest in securities with an average duration no longer than one year; that is, it replicates the overnight IBR rate calculated and published by the Central Bank on business days and securities that represent the interest rates for 90-day certificates of deposits (CDs) offered by private financial corporations. This category has the highest cash balances.

Category 3: "*Debt*" is comprised primarily of debt securities that might have an average duration of longer than one year. This category has the highest positive weights for the IBR and the securities that follow the inflation rate and Government bills. This category, which has a mix of these types of debt classes, suggests that the duration of an investment should be longer than one year. This category also has exposure to cash balances.

Category 4: "*Balanced*" is comprised principally of investments that follow a balanced portfolio with the highest positive weights in Government bills and liquid stocks. This category pursues a dynamic strategy of increasing exposure to Government debt and the most liquid stocks listed on the Colombian stock exchange. This category also has exposure to cash to balance the portfolio.

Category 5: "*Income*" is comprised primarily of liquid stocks and exposure to debt asset classes. This category represents investment funds that have the highest positive weights in the COLCAP index, followed by representative proportions of cash balances and debt asset classes (Legatruu). These funds invest in relatively the most liquid stocks listed on the Colombian stock exchange and debt assets. When exposure to COLCAP increases, these funds intend to compensate their portfolios with cash balances and debt asset classes in the same proportion.

5.3.5. Calculating customized benchmark return based on prospectus composition style

The use of a portfolio-based style analysis requires knowledge of the composition of the managed portfolio and the performance benchmark at the time of the analysis (Grinblatt and Titman, 1993; Arik and Jagannathan, 2002; Wermers, 2011). For instance, for a Colombian investment fund, an investor can obtain part of this information from monthly or annual reports. Some trust company websites also provide information on mutual fund characteristics, but this information is not entirely disclosed, and investor needs to be proficient in identifying portfolio composition and classifying funds into various categories.

Portfolio-based style analysis requires information on portfolio composition, which may be difficult to obtain. In our analysis, we intended to obtain information on portfolio composition using available data, monthly or annual reports, legal prospectuses, and trust company websites to understand the characteristics or attributes of the securities in which the manager has invested.

Obtaining this information was not easy. Our ultimate goal is to determine whether investors have enough information to evaluate fund performance in the Colombian market. Therefore, in this section, we use the information that we extracted from technical reports on portfolio fund composition classified by income to apply Sharpe's methodology based on mapping fund performance on broad indices' returns as an alternative measure to determine performance benchmark considering portfolio composition. The purpose is to permit a power comparison with the benchmark return calculated in Equation (7) (previous method 3) and evaluate whether investors with this information can evaluate investment performance.

The portfolio funds' composition by type of income described in the technical reports does not exactly represent the portfolio holdings of investment funds in Colombia because advisory companies are not obliged to report such information. However, we believe that these data are a good approximation for inferring a broad asset class that is underlined by this type of income. This does not mean that we will apply the methodology based on portfolio holdings, similar to in Grimblatt and Titman (1989), because the breakdown of portfolio holdings that we have for each fund is very broad and imprecise.

Panel A of Table 16 provides the average weights of the portfolio fund composition by type of income as captured from the prospectuses or technical reports for selected funds and the average of the weights for all investment funds. Panel B of Table 16 provides the summary statistics of portfolio fund composition by type of income and the passive benchmark of the broad asset classes that we assigned to each individual type of income. This information is used to determine the performance benchmark based on the portfolio-based style that represents, according to the public information, the best approximation of advisory companies' investment opportunity set and provides insights into investment fund performance in Colombia.

As we may observe, the portfolio fund composition by type of income on average corresponds to approximately 35% of investments tied to a fixed rate that regularly follows the COLTES (Colombian Government T-bills); investments tied to time deposit assets (DTF) represent approximately 15%, corresponding regularly to investments with a duration shorter than one year; investments tied to inflation rates (IPC) and overnight interbank rates (IBR) are 10% and 11%, respectively; approximately 13% of portfolio investments correspond to equity income; and portfolio investments in cash represent on average approximately 9%. According to the composition of investment funds by type of income as reported by the company's advisors, we encounter that the Colombian investment fund industry is heavily weighted toward fixed income assets that follow COLTES and

IPC. This industry is also heavily weighted toward money market assets (DTF and IBR), which account for an average of more than 74% of the total asset portfolio. On average, only 13% of portfolios are equity and 9% are held in cash to balance the portfolios.

Table 16: Weights´ average of the portfolio fund´s composition by type of income captured from the technical reports for some selected funds and summary statistics of the portfolio fund´s composition by all investment funds:

Panel A: Weights´ average of the portfolio fund´s composition by type of income captured from the technical reports for some selected investment funds

	Porfolio´s Funds Composition by type of Income obtained from Prospectus												
fund_code	Fixed Rate	DTF	UVR	IPC	IBR	Equity	Securities	Other Funds	Real Estate	Cash	Factoring	Others	Total
2276	0.00	0.00	0.15	0.00	0.00	91.01	0.00	8.84	0.00	0.00	0.00	0.00	100
2852	17.73	21.55	1.99	6.87	15.51	0.00	0.01	0.00	0.00	35.60	0.64	0.00	100
2971	23.36	24.90	5.56	14.69	15.91	0.48	0.38	0.00	0.00	14.61	0.06	0.00	100
2990	22.87	22.42	4.60	16.41	17.56	0.19	0.38	0.00	0.00	15.48	0.02	0.00	100
3010	22.87	22.42	4.60	16.41	17.56	0.21	0.38	0.00	0.00	15.48	0.02	0.00	100
3019	22.87	22.42	4.60	16.41	17.56	0.42	0.38	0.00	0.00	15.27	0.02	0.00	100
3031	22.87	22.42	4.60	16.41	17.56	0.21	0.38	0.00	0.00	15.48	0.02	0.00	100
3040	22.87	22.42	4.60	16.41	17.56	0.42	0.38	0.00	0.00	15.27	0.02	0.00	100
3049	24.28	26.55	1.39	17.25	18.05	0.39	0.36	0.00	0.00	11.57	0.13	0.00	100
3078	10.87	2.61	1.34	5.87	6.22	57.46	8.74	0.00	0.00	6.90	0.00	0.00	100
3644	0.00	0.00	0.49	0.00	0.00	78.97	9.10	0.00	0.00	11.44	0.00	0.00	100
3685	0.00	0.00	0.50	0.00	0.00	78.40	9.57	0.00	0.00	11.52	0.00	0.00	100
3721	16.72	44.93	14.27	5.36	10.57	0.00	0.00	0.00	0.00	8.16	0.00	0.00	100
3781	19.52	37.05	4.14	6.06	10.85	0.00	0.00	0.00	0.00	22.37	0.00	0.00	100
3794	86.90	0.00	2.23	0.00	0.00	0.00	0.00	0.00	0.00	9.56	1.31	0.00	100
…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…
31508	17.66	17.94	15.05	26.66	10.07	0.00	0.00	0.00	0.00	12.63	0.00	0.00	100
33186	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	100
33187	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	100
33355	94.79	0.00	0.00	0.00	0.00	0.00	0.00	4.49	0.00	0.69	0.00	0.00	100
33640	37.34	0.00	0.00	0.00	0.00	0.00	0.00	7.80	52.48	2.32	0.00	0.00	100
33642	27.45	0.00	0.00	0.00	0.00	0.00	0.00	6.26	59.41	6.82	0.00	0.00	100
33643	0.00	0.00	0.00	0.00	0.00	97.72	0.00	0.00	0.00	2.28	0.00	0.00	100
34166	9.00	0.00	91.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100
34908	0.00	0.00	0.00	0.00	0.00	99.90	0.00	0.00	0.00	0.10	0.00	0.00	100
36570	58.41	8.83	0.00	6.07	10.55	0.00	0.00	0.00	0.00	16.14	0.00	0.00	100
37238	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	100
37240	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	100
41248	38.38	22.51	0.00	13.47	25.64	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100
51954	90.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.75	0.00	0.00	100
51959	83.83	0.00	0.00	0.00	0.00	9.94	0.94	0.00	0.00	5.27	0.00	0.00	100

Panel B: Summary statistics of the portfolio fund´s composition by type of income and the passive benchmark on broad asset classes we assigned to each individual type of income to determine the performance benchmark based on portfolio-based style

Fund composition by Type of Income	N	mean	sd	min	p25	p50	p75	max	**Benchmark selected**
Fixed Rate	9087	35.39	32.50	0.00	10.93	25.59	50.00	100.00	r_coltes
DTF	9087	15.52	16.30	0.00	0.00	12.36	27.52	85.34	r_dtf_index
UVR	9087	2.51	10.20	0.00	0.00	0.01	1.63	91.00	r_coltesuvr
IPC	9087	9.70	14.18	0.00	0.00	6.55	15.18	100.00	r_cocpi_index
IBR	9087	11.63	13.15	0.00	0.00	7.26	21.14	66.00	r_colibr_index
Equity	9087	13.15	31.80	0.00	0.00	0.00	0.00	100.00	r_colcap_index
Securities	9087	0.42	2.76	0.00	0.00	0.00	0.00	30.79	r_legatruu
Other Funds	9087	0.44	2.51	0.00	0.00	0.00	0.00	58.00	r_coltes
Real Estate	9087	2.36	14.87	0.00	0.00	0.00	0.00	100.00	r_pei_index
Cash	9087	8.65	15.14	0.00	0.00	0.00	12.24	100.00	r_tcc_rate
Factoring	9087	0.19	1.49	0.00	0.00	0.00	0.00	25.47	r_dtf_index
Others	9087	0.03	0.59	0.00	0.00	0.00	0.00	24.55	r_dtf_index

Panel A shows the weights´ average of the portfolio fund´s composition by type of income captured from the technical reports for some selected funds from June 2009 to December 2015. Panel B shows the summary statistics of the portfolio fund´s composition by type of income and the passive benchmark on broad asset classes we assigned to each individual type of income to determine the performance benchmark based on portfolio-based style by all investment funds managed by Trust Companies in the Colombian market from June 2009 to December 2015. The definition of the type of income is as follows: Fixed rate is the type of income associated to securities assets in the Colombian markets that are priced at a fixed rate interest and regularly follows the COLTES. DTF is an interest rate composite, calculated as the weighted average of the interest rates on 90- day Certificates of Deposits (CDs) offered by Colombian banks and financial institutions. UVR (Unidad de Valor Real) is an index that has been designed to provide investors the general evolution of the mortgage market in Colombia, which can be used to measure the Colombian Government bonds “B TES securities linked to UVR”. IBR is the reference index employed to follow the development of the Colombian Money Market. It replicates an investment that produces the Overnight IBR rate (Inter Bank Rate) that is calculated and published by the Central Bank daily. Equity is the reference to represent the portfolio fund investments in companies listed in the Colombian stock exchange. Securities is the reference to represent the portfolio fund investments in different type of securities in the Colombian market without given more detail of the type of security. Other funds are the reference to represent portfolio fund investments in other investment funds. Real Estate is the reference to represent the portfolio fund investments in real estate assets. Cash is the to reference to represent the portfolio fund investments that are held in cash. Factoring is the reference to represent the portfolio fund investments that are comprised in the purchasing of account receivables. Others is the reference to represent the portfolio fund investments that are not framed in the previous descriptions. *N* in the table refers to the number of observations from year 2009 to year 2015. N in the table refers to the number of observations from year 2009 to year 2015.

Using the weights in Panel A of Table 16 for each fund, we construct additional benchmark returns using the portfolio composition based on income, as follows:

$$\boldsymbol{P_{i,t}} = \sum_{\boldsymbol{i}}\left(\left[\boldsymbol{\bar{\omega}_{1,\mathrm{i}}} \times \ \boldsymbol{x_{1,t}}\right] + \left[\boldsymbol{\bar{\omega}_{2,\mathrm{i}}} \times \ \boldsymbol{x_{2,t}}\right] + \cdots \left[\boldsymbol{\bar{\omega}_{J,i}} \times \ \boldsymbol{x_{J,t}}\right]\right) \qquad (13)$$

where $\boldsymbol{P_{i,t}}$ represents the returns on the prospectus style benchmark for fund *i* in month *t* based on the portfolio-based style, that is, the benchmark return representing the style of the investment fund's overall portfolio for fund *j* given the portfolio fund composition by income as reported in prospectuses and technical reports; $\bar{\boldsymbol{\omega}}_{\boldsymbol{i}}$ represents the weight reflected in Panel A of Table 16 of fund *i* for each type of income (asset) obtained in the technical reports that sum to 1 or 100%; and $\boldsymbol{x_{J,t}}$ represents the return on the passive benchmark index portfolio in month *t.* The terms in brackets represent the benchmark returns that can be attributed by its exposure to the different style benchmarks based on portfolio fund composition, that is, the return on the resultant portfolio-based style calculated for month *t* that reflects the investment opportunity set by the advisory companies.

Because the time series in the sample are rather short, we use one period (the available months in the sample periods) to estimate the parameters used in the style benchmark.

Equation (13) suggests a procedure to construct customized benchmark returns for each fund using the corresponding portfolio composition based on income. Table 17 provides the summary statistics of the customized benchmark for some selected investment funds and the average of the total investment funds managed by trust companies in the Colombian market. The customized benchmark or the return of the resultant portfolio composition based on income is calculated for each month *t* for all investment funds during the sample period.

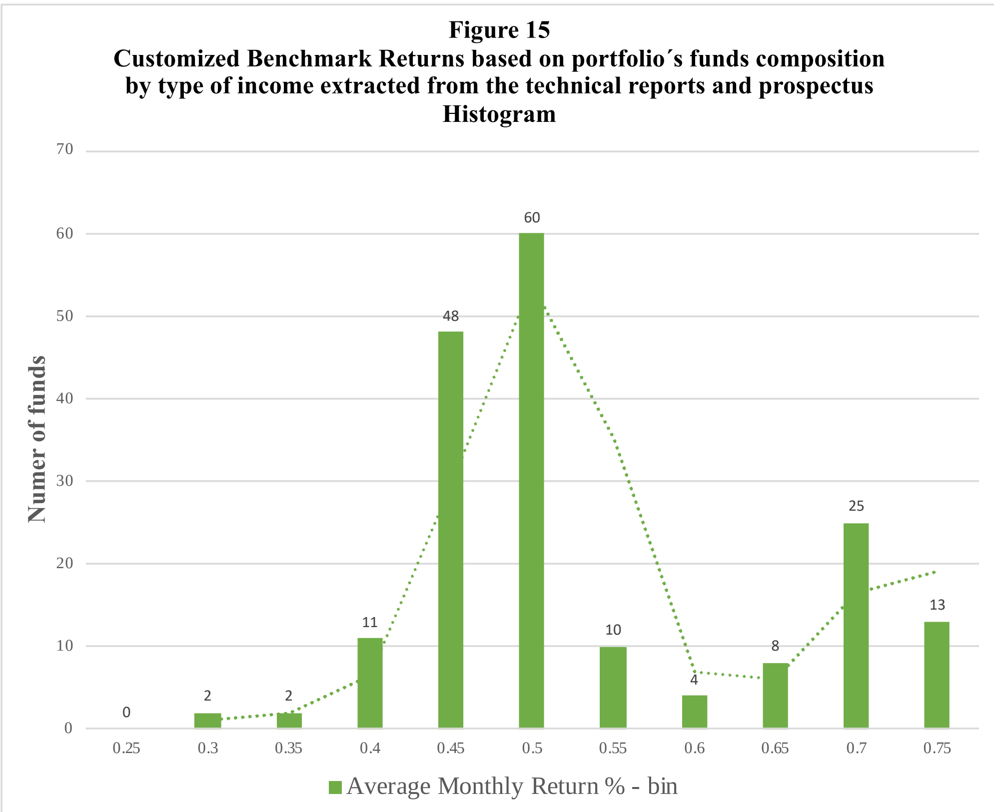
Table 17: Summary Statistics of customized Benchmark Returns based on portfolio-based style using the portfolio´s funds average weights by type of income extracted from the technical reports and prospectus for some selected investments funds and the average of all investment funds.

fund_code	N	mean	sd	min	p25	p50	p75	max
2276	84	0.486	4.158	-8.370	-2.287	-0.045	3.346	10.350
2852	84	0.414	0.323	-0.531	0.181	0.436	0.620	1.258
2971	84	0.449	0.447	-0.947	0.189	0.491	0.711	1.593
2990	84	0.441	0.426	-0.877	0.186	0.475	0.679	1.530
3010	84	0.441	0.426	-0.878	0.187	0.475	0.679	1.530
3019	84	0.441	0.429	-0.885	0.193	0.475	0.683	1.533
3031	84	0.441	0.426	-0.878	0.187	0.475	0.679	1.530
3040	84	0.441	0.429	-0.885	0.193	0.475	0.683	1.533
3049	84	0.436	0.422	-0.796	0.174	0.471	0.694	1.505
3078	84	0.442	2.721	-5.178	-1.351	0.197	2.224	6.831
3644	84	0.425	3.635	-7.064	-1.957	-0.039	2.845	8.832
3685	84	0.424	3.613	-7.007	-1.948	-0.036	2.827	8.789
3721	84	0.470	0.430	-1.029	0.234	0.503	0.703	1.794
3781	84	0.437	0.370	-0.692	0.181	0.470	0.647	1.434
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
33187	84	0.463	4.518	-9.107	-2.599	-0.145	3.633	11.018
33355	84	0.720	1.601	-3.778	-0.489	0.835	1.757	5.225
33640	84	0.537	1.107	-2.190	-0.123	0.681	1.354	3.005
33642	84	0.496	1.064	-2.161	0.130	0.707	1.232	2.823
33643	84	0.460	4.415	-8.891	-2.532	-0.134	3.557	10.774
34166	84	0.722	1.283	-4.161	0.150	0.611	1.417	4.677
34908	84	0.463	4.514	-9.098	-2.596	-0.144	3.629	11.008
36570	84	0.561	0.948	-2.110	-0.159	0.614	1.152	3.197
37238	84	0.387	1.437	-3.488	0.664	0.916	1.063	2.791
37240	84	0.387	1.437	-3.488	0.664	0.916	1.063	2.791
41248	84	0.487	0.627	-1.296	0.027	0.549	0.852	2.216
51954	84	0.684	1.458	-3.408	-0.412	0.785	1.621	4.775
51959	84	0.671	1.557	-3.488	-0.232	0.693	1.663	4.241
Average	**84**	**0.508**	**1.257**	**-2.657**	**-0.313**	**0.495**	**1.324**	**3.659**

This table presents the summary statistics of customized benchmark Returns based on portfolio-based style using the portfolio´s funds average weights by type of income extracted from the technical reports and prospectus for some selected investments funds and the Average of all investment funds. N in the table refers to the number of observations in months from year 2009 to year 2015.

As observed in Table 17, the average customized benchmark return using the portfolio's fund composition by type of income in the prospectus represents 0.51% per month, with an average standard deviation of 1.26%. Figure 15 represents graphically that these benchmark returns are more spread. Fifteen funds (8% of the total investment funds investigated) have on average a benchmark return between 0.3% and 0.4% per month; 118 funds (64% of the total investment funds) have on average a benchmark return between 0.45% and 0.55% per month; and 50 funds (27% of the total investment funds) have on average a benchmark return between 0.6% and 0.75% per month.

Figure 15: Histogram of customized Benchmark Returns based on portfolio-based style using the portfolio´s funds average weights by type of income extracted from the technical reports and prospectus – All investment funds



Taken together, Tables 12 and 17 and Figures 14 and 15 show that, in aggregate, the customized benchmark obtained using the portfolio's fund composition in the prospectus by type of income has an average monthly return (0.51%) higher than the customized benchmark based on Sharpe-implied portfolio weights (0.36%) but also has a much higher dispersion of 1.26% and 0.49%, respectively.

This result might be counterintuitive because, if investment fund managers might want to intentionally modify the weights reported in the technical reports, they choose to report portfolio weights that lead to infer passive benchmarks that are easy to beat (lower returns), which also lead to inferring a higher alpha in the performance evaluation. Therefore, the results to date suggest that, at the aggregate level, the portfolios reported by the investment fund manager are nosier but do not follow a default strategy to "deceive" investors.

As we can see, the use of the portfolio composition based on income according to prospectuses also provides a natural method for constructing benchmarks that meet the requirements mentioned in the previous points. The benchmark obtained is the result of the returns that aggregate the individual securities using available information for investors in Colombia (portfolio-based composition by type of income) that allow us to evaluate and observe how the investment funds investigated empirically behave based on the realized returns.

These results emphasize the advantage that we gained by being the first in Colombia to use the only available public information on portfolio composition. This customized style benchmark return can also be applied directly to measure the efficacy with which the investment fund manager performs his or her functions. In the next chapter, we employ this benchmark return to permit a power comparison with the other benchmark returns computed in Equation (7) to evaluate the value added or lost from asset allocation decisions.

5.3.6. Comparison between benchmark returns

At this stage, we have analyzed the average monthly returns of the customized benchmarks. We focus on the risk to enable a power comparison between the benchmarks calculated in Equations (7) and (13). The return obtained by a fund in each month t is correlated with, in each month t, i) the customized benchmark return based on the Sharpe implied portfolios weights (Equation 7); and ii) the customized benchmark return based on the portfolio composition in the prospectus (Equation 13).

Figure 16 shows the i) correlation between the fund's return and the customized benchmark return based on the Sharpe implied portfolios weights; and ii) correlation between the fund's return and the customized benchmark return based on the portfolio composition in the prospectus. In addition, Figure 17 shows the correlation between benchmarks. Table 18 provides the average summary statistics of the correlation matrix result between fund returns and customized benchmark returns based on the Sharpe implied portfolios weights and the customized benchmark return based on the portfolio's composition in the prospectus.

Figure 16: Correlation graph between fund return and customized benchmark returns based on Sharpe implied portfolios weights; and customized benchmark return based on Prospectus

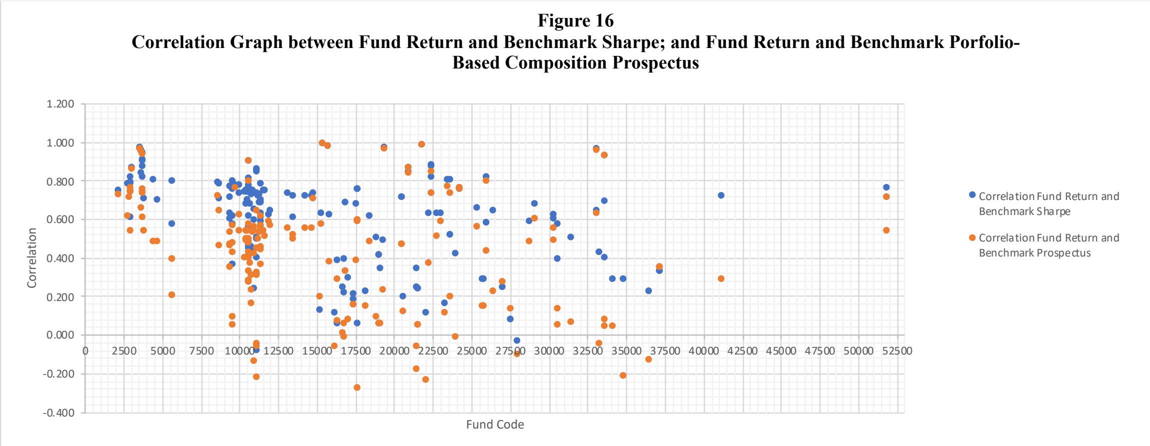


Figure 17: Correlation graph between customized benchmark returns based on Sharpe implied portfolios weights and customized benchmark return based on portfolio-based composition according to prospectus

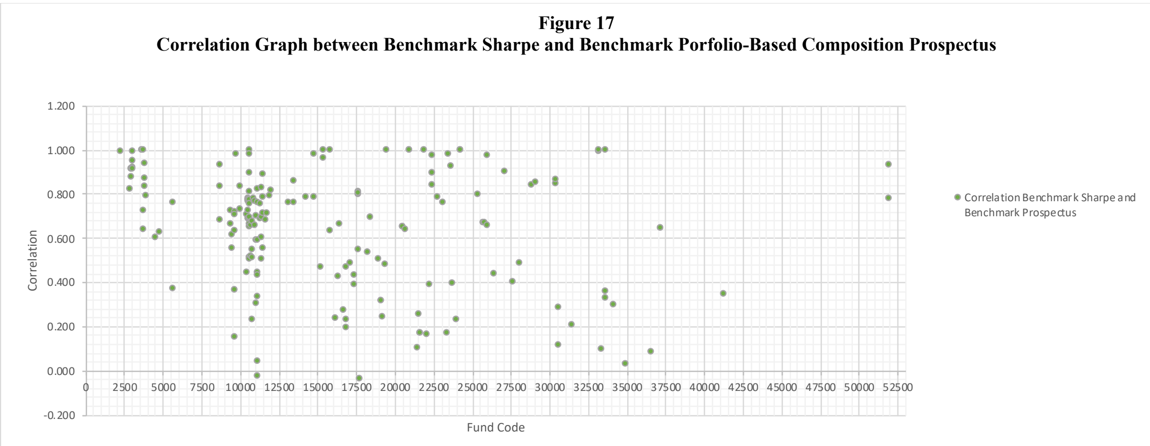


Table 18 presents interesting correlation results between the two customized benchmarks calculated in the previous points. As Table 18 shows, the average correlation results between fund returns and customized benchmark returns based on Sharpe is 0.618, with a standard deviation of 0.229/. The correlation result between fund returns and customized benchmark returns based on the portfolio composition in the prospectus is 0.429, with a standard deviation of 0.286. Thus, the correlation between fund returns and the customized benchmark based on Sharpe is much higher than the correlation using the benchmark based on the prospectus. In addition, the correlation using the benchmark based on the prospectus is noisier. In contrast, a comparison of the number of cases (funds) for which the correlation results between fund returns and customized benchmark returns based on Sharpe is greater than the correlation using the customized benchmark return based on the prospectus shows that, in 96.7% of the cases (Column 4 of Table 18), the correlation using the customized benchmark returns based on Sharpe is higher than the correlation using the customized benchmark returns based on the prospectus.

Table 18: Average Summary Statistics of Correlation Matrix between fund return and customized benchmark returns based on Sharpe implied portfolios weights; and customized benchmark return based on portfolio-based composition according to prospectus

Summary Statistics	N	Correlation Fund Return and Benchmark Sharpe	Correlation Fund Return and Benchmark Prospectus	rho_Benchmark_Sharpe > rho_Benchmark_Prospectus	Correlation Benchmark Sharpe and Benchmark Prospectus
Average	**62**	**0.618**	**0.429**	**0.967**	**0.647**
SD	**19**	**0.229**	**0.286**	**0.178**	**0.262**
Min	24	-0.082	-0.276	0.000	-0.036
p25	47	0.491	0.215	1.000	0.481
p50	66	0.699	0.483	1.000	0.691
p75	81	0.765	0.591	1.000	0.837
Max	81	0.989	0.987	1.000	1.000

This table presents the average summary statistics of the correlation matrix results: column 3 is the correlation results between fund return and customized benchmark return based on Sharpe implied portfolios weights; column 4 is the correlation results between fund return and customized benchmark return based on portfolio-based composition according to prospectus; column 5 shows that the correlation results between fund return and customized benchmark return based on Sharpe implied portfolios weights (column 3) is greater in the 96.7% of the cases with the correlation made using the customized benchmark return based on portfolio-based composition according to prospectus (column 4); and column 6 is the correlation results between customized benchmark return based on Sharpe implied portfolios weights and customized benchmark return based on portfolio-based composition. N in the table refers the number of average observations in months of each investment funds from year 2009 to year 2015.

This result is important for our study because this high correlation justifies our work and emphasizes the advantage that we have gained by computing the corresponding asset mix to analyze the style benchmark returns based on the Sharpe (1992) constrained regression. In particular, in this case, we find that the positive loadings have been estimated with accuracy. Figures 16 and 17 graphically emphasize the high correlation that exists between fund returns and customized benchmark returns based on Sharpe-implied portfolio weights.

However, we observe in Figure 16 that some negative or very low correlations of some funds exist between fund returns and customized benchmark returns based on the prospectus. This negative or low correlation results from those funds having important differences between the weights reported for the portfolio composition in the prospectuses or technical reports, and the positive weights that were estimated in Equation (5) as the style of the individual investment funds. For instance, funds “11169” and “17727” report in the prospectus a portfolio composition of 100% equity, whereas the estimated weight as the fund’s style is 100% IBR (money market); fund “28076” reports in the prospectus a portfolio composition of 100% fixed rate (COLTES), whereas the estimated weight as the style of the fund is 66% IBR and 34% TCC (money market); fund “16412” reports in the prospectus a portfolio composition of 100% equity, whereas the estimated weight as the style of the funds is 94% TCC (securities represented in cash); fund “27627” reports in the prospectus a portfolio composition of 100% fixed rate (COLTES), whereas the estimated weight as the style of the fund is 98% TCC (securities represented in cash); fund “22119” reports in the prospectus a portfolio composition of 75% fixed rate (COLTES) and 25% equity, whereas the estimated weight as the style of the fund is 100% IBR (money market); fund “16211” reports in the prospectus a portfolio composition of 76% COLTES UVR, whereas the estimated weights as the style of the fund are 36% IBR, 45% TCC, and 14% inflation; fund “15252” reports in the prospectus a portfolio composition of 90% fixed rate (COLTES), whereas the estimated weights as the style of the fund are 59% TCC (cash) and 34% equity; fund “17402” reports in the prospectus a portfolio composition of 100% fixed rate (COLTES), whereas the estimated weights as the style of the fund are 68% IBR and 29% TCC (money market); fund “23347” reports in the prospectus a portfolio composition of 94% fixed rate (COLTES), whereas the estimated weights as the style of the fund are is 37% IBR and 62% TCC (money market); fund “17403” reports in the prospectus a portfolio composition of 100% in fixed rate (COLTES), whereas the estimated weights as the style of the fund are 61% IBR and 36% TCC (money market); and fund “20660” reports in the prospectus a portfolio composition of 95% in fixed rate (COLTES), whereas the estimated weight as the style of the fund is 93% TCC (cash).

These differences between the realized return and the portfolio fund’s composition reported by income type emphasize that the condition of the information reported by the advisory company or the information that investors have on hand to evaluate the performance of their investment is not precise, misleading, or too generic. For this additional reason, we conclude that the style classification provided by the regular and the company's advisors does not allow investors to explain differences in future returns and evaluate the performance of their investment.

Finally, our findings provide evidence that investment fund returns in Colombia are less correlated with the customized benchmark based on public information (portfolio fund composition by type of income according to prospectuses or technical reports) than with the customized benchmark based on our empirical style classification (Sharpe-implied portfolios weights). Thus, on average, the traded indices in technical reports are more difficult to beat but also more strongly associated with active management or at least less representative of the passive strategy of investment funds.

Therefore, to confirm whether investors have enough information to evaluate fund performance in the Colombian market or whether an intentional strategy might exist to alter the portfolio weights in the technical reports or prospectuses, in the next chapter, we focus on investigating investment fund performance by calculating alpha using the customized benchmarks (based on a portfolio's fund composition according to prospectuses or technical reports and based on the Sharpe-implied portfolios weights) and then compare them.

In the next chapter, if the alpha we obtain using the customized benchmarks based on a portfolio's fund composition—according to prospectuses or technical reports—is systematically higher, we might interpret this result as an evidence of "cheating" investors with the likely intention to alter alpha because fund managers might show portfolio weights that do not correspond with the true strategy of the investment fund according to our empirical model (Sharpe-implied portfolios weights). However, based on our results to this point, we have no evidence that the portfolio weights reported in the technical reports are intentionally altered to "cheat" investors. However, they are noisier and provide a clear idea of investment fund performance for investors.

5.4. Interpretations

To summarize our results, the findings are consistent with prior research (Brown et al., 1997; Sharpe, 1992) because the empirical style classification formed via past returns and clusters may agree or disagree with the standard industry classification. However, in our case, the absence of an industry classification for investment funds in Colombia and the too generic nature of the information provided to investors are evidence that the local classification provided by either the company advisory or even the regulator has relatively little power to explain differential fund performance.

The empirical style classification we followed identifies five major types of fund strategies. As Brown et al. (1997) pointed out, the fund strategies may not exhaust the range of different fund managers but do provide an overview of the strategies that differentiate managers or advisory companies.

The major advantage of estimating positive and constrained coefficients on prespecified factors (Sharpe, 1992) is that doing so provides some insights into the composition and behavior categories (Brown and Goetzmann, 1997), especially when no publicly useful benchmarks exist to evaluate relative past performance for investment funds and when the portfolio fund's composition is not reported or is too generic. When the loadings are not constrained to be positive, our results are consistent with prior research because we find no evident advantage in terms of explanatory value. The disadvantage we find is when loadings on correlated indexes might have collinearity issues. In this case, the loadings will be estimated with inaccuracy.

Estimating positive and constrained coefficients on prespecified factors remains an informative and cost-effective analytical tool for investors interested in creating more relevant benchmarks and assessing the asset allocation implications of their mutual fund choices because it provides a consistent view of investment decisions made by managers on behalf of investors. This style analysis can serve as a valuable method to help investors achieve their goals in cost-effective ways (Sharpe, 1992).

Our findings from employing the empirical category classification algorithm contribute to the extant finance literature and show that investment funds in emerging markets can be categorized under this classification algorithm, which is consistent with commonly used asset pricing models. As Brown et al. (1997) pointed out, the advantage of using this method over heuristic classification is that researchers can use it to decompose styles into more familiar measures, such as time-varying factor loadings and risk premiums.

6. FUND PERFORMANCE ANALYSIS

Once the customized benchmark return in Equations (7) and (13) are computed and the style classification of investment funds has been carried out, we estimate the performance of Colombian investment funds from 2009 to 2015. As we described in section 3.2, given that our sample contains virtually all of the funds that existed during this period, the results should not be affected by survivorship bias.

6.1. Empirical methodology

During the evaluation of fund performance, we employ the following methods to evaluate funds' returns before expenses relative to the performance of the customized benchmarks for which superior results should justify the higher fees usually paid to active as opposed to passive managers.

6.1.1. Selection return

As described in the previous section, a passive fund manager provides investors with an investment style, whereas an active manager provides both style and selection (see Sharpe (1992)). This statement suggests that the performance benchmark should consist of a portfolio of asset classes that provides the desired exposure to benchmark style asset classes. As Sharpe (1992) pointed out, superior performance relative to the performance benchmark that provides a static mix of the style benchmark asset classes would justify the higher fees usually paid to active as opposed to passive managers.

We follow this approach and focus on the fund's selection return, which is defined as the difference between the fund's return and that of a passive mix with the same style—in our case, the customized benchmark returns (see Sharpe

(1992)). This approach also has been used by Christofferson and Musto (2002: page 1504), who gauged the actual persistence in money fund performance and calculated fund performance as the difference between the net return less the value-weighted index—the customized benchmark return in our case.

To illustrate this approach, we employ the following steps for each month *t*:

1. The fund's style is estimated by employing quadratic regressions using returns from the entire sample period (Equation 5);

2. The customized performance benchmark that provides a static mix of the style benchmark asset classes is calculated for month *t* (Equation 7); and,

3. The difference between the actual fund's return in month *t* and that of the customized style benchmark determined in the previous steps is computed (Equation 7). This difference is defined as the fund's *selection return* for month *t*.

Based on the description in the previous section, the manager on behalf of investors is assumed to make decisions that result in an effective asset mix and a set of selection returns. In this sense, the investor should select a manager that may act passively or actively and should select a specific allocation of funds among such managers (see Sharpe (1992)).

The procedures previously described can be applied directly to measure the efficacy with which the manager performs his or her functions on behalf of investors. The performance of each monthly fund's return can be compared with that of a predetermined customized benchmark associated with the asset mix to assess the value added or lost because of the asset allocation decisions. As Sharpe (1992) pointed out, the remainder of the investor's return is attributable to the joint effects of i) fund managers' selection returns, and 2) the investor's allocation of money among managers. Using the results of Equation (7) and the monthly fund return, we can derive the selection return as follows:

$$\boldsymbol{SR_{j,t}} = \boldsymbol{R_{j,t}} - \boldsymbol{S_{j,t}} \tag{14}$$

where $\boldsymbol{SR_j}$ is the selection return for fund *j;* $\boldsymbol{S_{j,t}}$ is the customized benchmark return representing the style of the investment fund's overall portfolio for fund *j* in month t; and $\boldsymbol{R_{j,t}}$ is the actual fund's return in month t. The selection return for fund *j* is proven by the t-statistic test. The t-statistic is computed by dividing the average return difference by the standard error of the mean. As Sharpe (1992) pointed out, the t-statistic is closely related to the reward-to-variability ratio (sometimes called the Sharpe Ratio) for the active component of a fund's return, which is simply the mean value divided by the standard deviation.

6.1.2. Risk-adjusted return using the customized benchmark return

Alternatively, we want to evaluate fund performance by decomposing a fund's return into the systematic part, which can be replicated by the customized benchmarks, and the nonsystematic part, referred to as the risk-adjusted performance. We are interested in evaluating the part of the return that cannot be attributed to general risk taking (Magnus et al., 2000).

We regress the monthly fund's returns before expenses on the customized benchmark return representing the style of the investment fund's overall portfolio for fund *j* in month *t*, which is computed in Equation (7). This customized benchmark is closely aligned with the fund's style based on the best asset class mix. This method is sometimes termed the Sharpe-Lintner CAPM measure (Jensen alpha), which in our case permits a power comparison with the selection return method. The model specification is as follows:

$$\boldsymbol{R_{j,t}} - \boldsymbol{r_{f,t}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_{\mathrm{j}} \left(\boldsymbol{S_{j,t}} - \boldsymbol{r_{f,t}} \right) + \boldsymbol{\varepsilon_j} \tag{15}$$

where $\boldsymbol{R_{j,t}}$ is the monthly return before of expenses for fund *j* in month *t*; $\boldsymbol{r_{f,t}}$ is the risk-free rate; and $\boldsymbol{S_{j,t}}$ is the customized benchmark return representing the style of the investment fund's overall portfolio for fund *j* in month *t*. We use as a risk-free rate the Colombian short-term bills (COLTES CP).

In addition to and to permit a power comparison with the previous model, instead of regressing the monthly fund's returns on the customized benchmark based on the Sharpe weights computed in Equation (7), we regress monthly fund returns on the approximated benchmark returns based on the prospectus weights calculated in Equation (13). This approximated benchmark is more closely aligned with the resultant portfolio-based style that reflects the investment opportunity set and is reported by advisory companies in their technical reports.

The model specification is as follows:

$$\boldsymbol{R_{j,t}} - \boldsymbol{r_{f,t}} = \boldsymbol{\alpha} + \boldsymbol{gamma}_{\mathrm{j}} \left(\boldsymbol{P_{j,t}} - \boldsymbol{r_{f,t}} \right) + \boldsymbol{\varepsilon_i} \tag{16}$$

where $\boldsymbol{R_{j,t}}$ is the monthly return before expenses for fund *j* in month *t*; $\boldsymbol{r_{f,t}}$ is the risk-free rate; and $\boldsymbol{P_{j,t}}$ the approximated benchmark return based on a portfolio-based composition according to prospectuses and technical reports, which represents the style of the investment fund's overall portfolio reported by advisory companies for fund *j* in month *t*. We also use as a risk-free rate the short-term Colombian bills (COLTES CP).

In both cases, we obtain an estimated single alpha (the deviation from the benchmark model) using returns from the entire sample period. A positive (negative) alpha is interpreted as overperformance (underperformance) and measures the performance relative to simple trading rules that individual managers could implement.

To construct a panel of monthly rolling alphas or monthly risk-adjusted performance estimates using the customized benchmark returns, we re-express Equations (15) and (16) following the two-stages estimation procedures described in Carhart (1997) and Gil-Bazo et al. (2009).

In the first stage, we rolling-regressed the excess returns of each fund every month *t* during the years 2009 to 2015 and consider the benchmark return over the previous 24 months. The excess return for each fund is computed as the difference between the fund return and the risk-free rate for the short-term Colombian bills (COLTES CP). Given the monthly time series data that we have for investment funds, we require funds to be in the sample for at least 24 months and then run the rolling regression using the available data.[28]

In the second stage, we estimate the risk-adjusted performance for each fund in month *t*. The fund's risk-adjusted performance is estimated in two steps. First, we estimate the realized risk premium or predicted excess return for month *t*, which is computed using the vector of betas estimated (for the Sharpe and the

[28] In our choice, we use an estimation period of two years instead of the estimation period of five years employed by Gil-Bazo et al. (2009) or the three-year period used by Carhart (1997). Given the limited monthly time series data that we have, we could not use a longer estimation period for the monthly data-panel of risk-adjusted performance estimates for each fund. As described by Gil-Bazo et al. (2009), a longer estimation period might reduce sampling errors in betas and mitigate the effect of omission bias and incubation bias, also described by Elton, Gruber, and Blake (2001) and Evans (2009).

prospectus benchmarks) times the vector of factor realizations or fund excess return in month *t.* Second, we calculate the risk-adjusted performance for each fund in month *t* by taking the difference between the excess return of each fund and the predicted excess return (or realized risk premium) calculated in the previous first step.

6.1.3. Risk-adjusted return using the three Fama-French factors

As a robustness analysis and to permit a power comparison with the previous equity funds model, we separately estimate the risk-adjusted returns to test the performance for funds classified under the "equity" category as defined in the style classification category section. In this sense, we regress the portfolio returns of equity funds on the three Fama-French factors.[29] This method allows us to control for potential errors, risk factors, and the momentum factor. This model has been used from Carhart (1997) onwards and has been shown to have good explanatory power only for equity funds for the observed cross-section of fund returns. The model specification is as follows:

$$\boldsymbol{Y_i - r_f = \alpha + \beta_1 \left(\mathbf{MKT} - r_f\right) + \beta_2(\mathbf{SMB}) + \beta_3(\mathbf{HML}) + \beta_4(\mathbf{UMD}) + \varepsilon_i} \tag{17}$$

where Y*i* is the fund return net of expenses for fund *i*; $\boldsymbol{r_f}$ is the risk-free rate; and the four risk factors are denoted by *MKT* (market portfolio), *SMB* (size portfolio), *HML* (book-to-market portfolio), and *UMD* (momentum portfolio). We use as a risk-free rate the Colombian short-term bills (COLTES CP). In this case, we also

[29] Data are obtained by Pedraza et al. (2017), who kindly provided us with the Fama and French risk factors and the momentum factor constructed by them for the stock market in Colombia and used in their study of: Do Foreign Investors Underperform? An Empirical Decomposition into Styles and Flows (2017).

obtain an estimated single alpha using returns from the entire sample period for equity funds.

To construct a panel of monthly rolling alphas or monthly risk-adjusted performance estimates using the three Fama-French factors, we re-express Equation (17) following the same procedure described in the previous section. First, we rolling-regressed excess returns for each fund on the three Fama-French factors during the previous 24 months. Second, we compute the risk-adjusted performance for each fund in month *t* by taking the difference between the excess return for each fund and the predicted excess return for month *t*, defined as the vector of betas of the three Fama-French factors times the excess return for each fund in month *t.*

6.2. Empirical results

Table 19 reports the results obtained from the selection return, the results of the out-of-sample cross-sectional regression that employed the customized benchmarks based on the Sharpe weights (Equation 7) and the style in the prospectus (Equation 13), and the results obtained from the Carhart four-factor model (Equation 17). The results correspond to the performance evaluation for the entire history of funds investigated.

In Panel A of Table 19, the first group of columns shows the mean difference computed in Equation (14), standard deviation, t-statistic for the selection results, positive and negative alphas, and the significant alpha at the 5% level. In Panel B of Table 19, the first and second groups of columns provide the single alpha estimation computed in Equation (15), t-statistic for alpha results, positives and negatives alphas, the significant alpha at the 5% level, beta of the variable (style customized benchmark Sharpe), and the $\boldsymbol{R}^2$ that results from the application of the regression analysis in Equation (15). The second group of columns in Panel B shows the rolling regression of monthly fund risk-adjusted performance estimates. This rolling regression yields a total of 6,980 monthly risk-adjusted returns. In Panel C of Table 19, the first and second groups of columns show the single alpha estimation computed using Equation (16), t-statistic for alpha results, positive and negative alphas, the significant alpha at the 5% level, beta of the variable (style customized benchmark in prospectuses), and the $\boldsymbol{R}^2$ that results from the application of the regression analysis in Equation (16). The second group of columns in Panel C shows the rolling regression of monthly fund risk-adjusted performance estimates. This rolling regression yields a total of 6,980 monthly risk-adjusted returns. In Panel D of Table 19, the first and second groups of columns show the single alpha estimation computed in Equation (17), t-statistic for alpha results, positive and negative alphas, the significant alpha at the 5% level, beta of the four factors (Carhart model), and the $\boldsymbol{R}^2$ that results from the application of the regression analysis in Equation (17). The results in this panel are only for equity funds. The second group of columns in Panel D shows the rolling regression of monthly fund risk-adjusted performance estimates. This rolling regression yields a total of 802 monthly risk-adjusted returns for equity investment funds.

Table 19: Summary Statistics Cross-sectional Performance of all Investment Funds Analysis – Selection Return analysis and Regressing returns employing the customized benchmarks based on Sharpe weights and based on the portfolio-based style, as well as the results obtained from the Carhart four factors model. Report t-values also for the regression coefficients.

Panel A: Summary Statistics Cross-sectional Performance of all Investment Funds Analysis – Selection Return analysis. Report positive and negatives alphas and t-values for mean results.

Summary Statistics	SELECTION RETURN						
	mean (Alpha)	SD	t_value	**ALPHA<0**	**ALPHA>0**	**Significant at 5% ALPHA<0**	**Significant at 5% ALPHA>0**
Average	**-0.021**	**0.395**	**-0.679**	**-0.141**	**0.207**	**-0.162**	**0.305**
SD	**0.314**	**0.676**	**7.563**	**0.290**	**0.216**	**0.334**	**0.210**
Median	**-0.031**	**0.102**	**-1.666**	**-0.056**	**0.115**	**-0.059**	**0.272**
Min	-2.013	0.041	-20.975	-2.013	0.004	-2.013	0.026
p25	-0.071	0.079	-4.679	-0.108	0.018	-0.105	0.146
p50	-0.031	0.102	-1.666	-0.056	0.115	-0.059	0.272
p75	0.021	0.308	1.348	-0.032	0.331	-0.040	0.392
p90	0.305	1.172	9.765	-0.018	0.537	-0.029	0.561
Max	0.973	3.902	26.329	-0.003	0.973	-0.015	0.973
Count	183	183	183	120	63	86	35

Panel B: Summary Statistics Cross-sectional Performance of all Investment Funds Analysis – Regressing returns analysis employing the customized benchmarks based on Sharpe weights calculated in equation (15) and rolling regression panel of monthly fund risk-adjusted performance estimates (Alpha estimated). Report positive and negatives alphas and t-values for the regression coefficients.

Summary Statistics	ALPHA USING SHARPE BENCHMARK																	
	SINGLE BETA ESTIMATION									ROLLING BETA ESTIMATION								
	ALPHA	ALPHA t-value	**ALPHA<0**	**ALPHA>0**	**Significant at 5% ALPHA<0**	**Significant at 5% ALPHA>0**	BETA	BETA t-value	R2	ALPHA_ESTIMATED	ALPHA_ESTIMATED t-value	**ALPHA<0**	**ALPHA>0**	**Significant at 5% ALPHA<0**	**Significant at 5% ALPHA>0**	BETA	BETA t-value	R2
Average	**-0.015**	**-0.678**	**-0.135**	**0.219**	**-0.156**	**0.337**	**1.014**	**53.433**	**0.878**	**-0.027**	**0.023**	**-0.156**	**0.230**	**-0.180**	**0.291**	**1.028**	**36.505**	**0.883**
SD	**0.310**	**7.283**	**0.276**	**0.229**	**0.323**	**0.210**	**0.099**	**36.044**	**0.203**	**0.391**	**7.257**	**0.388**	**0.242**	**0.484**	**0.207**	**0.141**	**25.583**	**0.189**
Median	**-0.031**	**-1.598**	**-0.055**	**0.139**	**-0.059**	**0.320**	**0.996**	**52.795**	**0.982**	**-0.040**	**-1.172**	**-0.062**	**0.194**	**-0.066**	**0.259**	**1.001**	**36.484**	**0.977**
Min	-2.008	-20.334	-2.008	0.002	-2.008	0.031	0.700	2.086	0.075	-2.882	-15.532	-2.882	0.003	-2.882	-0.003	0.784	1.989	0.156
p25	-0.076	-4.454	-0.110	0.019	-0.100	0.196	0.989	20.608	0.886	-0.079	-3.199	-0.106	0.035	-0.100	0.157	0.984	15.265	0.895
p50	-0.031	-1.598	-0.055	0.139	-0.059	0.320	0.996	52.795	0.982	-0.040	-1.172	-0.062	0.194	-0.066	0.259	1.001	36.484	0.977
p75	0.020	0.963	-0.032	0.355	-0.043	0.473	1.009	81.142	0.990	0.034	0.869	-0.040	0.305	-0.047	0.365	1.024	50.768	0.988
p90	0.321	9.333	-0.017	0.535	-0.029	0.556	1.034	101.591	0.993	0.284	8.745	-0.020	0.590	-0.032	0.593	1.089	62.682	0.993
Max	0.969	25.472	-0.001	0.969	-0.016	0.969	1.708	156.822	0.998	1.134	38.596	-0.003	1.134	0.727	0.892	2.284	196.487	0.999
Count	183	183	121	62	84	35	183	183	183	183	183	122	61	78	30	183	183	183

Panel C: Summary Statistics Cross-sectional Performance of all Investment Funds Analysis – Regressing returns analysis employing the customized benchmarks based on Prospectus in equation (16) and rolling regression panel of monthly fund risk-adjusted performance estimates (Alpha estimated). Report positive and negatives alphas and t-values for the regression coefficients.

Summary Statistics	ALPHA USING BENCHMARK FROM PROSPECTUS																	
	SINGLE BETA ESTIMATION									ROLLING BETA ESTIMATION								
	ALPHA	ALPHA t-value	**ALPHA<0**	**ALPHA>0**	**Significant at 5% ALPHA<0**	**Significant at 5% ALPHA>0**	BETA	BETA t-value	R2	ALPHA_ESTIMATED	ALPHA_ESTIMATED t-value	**ALPHA<0**	**ALPHA>0**	**Significant at 5% ALPHA<0**	**Significant at 5% ALPHA>0**	BETA	BETA t-value	R2
Average	**-0.113**	**-1.235**	**-0.193**	**0.213**	**-0.317**	**0.402**	**0.720**	**11.062**	**0.548**	**-0.099**	**-1.030**	**-0.225**	**0.211**	**-0.388**	**0.586**	**0.704**	**6.715**	**0.542**
SD	**0.324**	**1.934**	**0.297**	**0.206**	**0.407**	**0.197**	**0.741**	**13.212**	**0.324**	**0.416**	**1.521**	**0.406**	**0.243**	**0.622**	**0.361**	**0.714**	**8.609**	**0.299**
Median	**-0.080**	**-1.504**	**-0.101**	**0.145**	**-0.186**	**0.418**	**1.077**	**10.846**	**0.645**	**-0.069**	**-1.208**	**-0.101**	**0.146**	**-0.197**	**0.526**	**1.003**	**6.334**	**0.563**
Min	-2.126	-7.364	-2.126	0.000	-2.126	0.151	-0.906	-6.888	0.000	-2.895	-6.374	-2.895	0.004	-2.895	0.051	-0.758	-5.468	0.002
p25	-0.176	-2.435	-0.226	0.061	-0.322	0.217	-0.011	-0.328	0.258	-0.165	-2.021	-0.214	0.038	-0.314	0.446	-0.029	-0.289	0.306
p50	-0.080	-1.504	-0.101	0.145	-0.186	0.418	1.077	10.846	0.645	-0.069	-1.208	-0.101	0.146	-0.197	0.526	1.003	6.334	0.563
p75	-0.021	-0.435	-0.056	0.343	-0.104	0.507	1.341	19.725	0.853	0.015	-0.272	-0.063	0.299	-0.118	0.649	1.317	11.790	0.825
p90	0.139	1.208	-0.028	0.507	-0.076	0.520	1.412	24.501	0.915	0.192	0.717	-0.043	0.524	-0.082	0.953	1.384	16.265	0.918
Max	0.918	5.385	-0.003	0.918	-0.037	0.918	2.616	87.949	0.991	1.335	4.677	-0.001	1.335	0.178	1.335	1.856	64.160	0.994
Count	183	183	147	36	64	13	183	183	183	183	183	130	53	47	7	183	183	183

Panel D: Summary Statistics Cross-sectional Performance of all Investment Funds Analysis – Regressing returns analysis only for equity funds obtained from the Carhart four factors model calculated in equation (17) and rolling regression panel of monthly fund risk-adjusted performance estimates (Alpha estimated). Report positive and negatives alphas and t-values for the regression coefficients.

Summary Statistics	ALPHA USING CARHART 4-FACTOR MODEL (only equity funds) SINGLE BETA ESTIMATION														
	ALPHA	ALPHA t-value	**ALPHA<0**	**ALPHA>0**	**Significant at 5% ALPHA<0**	**Significant at 5% ALPHA>0**	BETA Market	BETA Market t-value	BETA SMB	BETA SMB t-value	BETA HML	BETA HML t-value	BETA UMD	BETA UMD t-value	R2
Average	**-0.785**	**-1.876**	**-0.935**	**0.319**	**-1.237**	**0.000**	**0.269**	**0.678**	**-45.215**	**-4.115**	**-3.957**	**0.032**	**-32.903**	**-2.818**	**0.364**
SD	**0.823**	**1.397**	**0.758**	**0.225**	**0.732**	**0.000**	**0.364**	**1.107**	**26.064**	**1.633**	**16.191**	**0.996**	**23.482**	**1.254**	**0.140**
Median	**-0.551**	**-2.437**	**-0.644**	**0.191**	**-1.337**	**0.000**	**0.340**	**0.997**	**-52.407**	**-4.104**	**-6.390**	**-0.153**	**-34.234**	**-3.002**	**0.400**
Min	-2.777	-3.915	-2.777	0.130	-2.777	0.000	-0.650	-2.834	-80.797	-7.557	-37.055	-1.757	-85.617	-5.242	0.113
p25	-1.351	-2.779	-1.358	0.161	-1.551	0.000	-0.007	-0.054	-68.457	-5.263	-14.214	-0.677	-49.571	-3.568	0.266
p50	-0.551	-2.437	-0.644	0.191	-1.337	0.000	0.340	0.997	-52.407	-4.104	-6.390	-0.153	-34.234	-3.002	0.400
p75	-0.137	-1.204	-0.406	0.413	-0.577	0.000	0.505	1.203	-16.630	-2.886	9.024	0.792	-12.456	-1.519	0.443
p90	0.054	0.190	-0.137	0.546	-0.412	0.000	0.704	1.800	-9.180	-2.417	16.453	1.324	-4.387	-1.060	0.528
Max	0.634	1.275	-0.061	0.634	-0.229	0.000	0.868	2.853	-2.127	-1.152	24.728	1.727	-1.511	-0.763	0.619
Count	25	25	22	3	15	0	25	25	25	25	25	25	25	25	25

Summary Statistics	ALPHA USING CARHART 4-FACTOR MODEL (only equity funds) ROLLING BETA ESTIMATION														
	ALPHA_ESTIMATED	ALPHA ESTIMATED t-value	**ALPHA<0**	**ALPHA>0**	**Significant at 5% ALPHA<0**	**Significant at 5% ALPHA>0**	BETA Market	BETA Market t-value	BETA SMB	BETA SMB t-value	BETA HML	BETA HML t-value	BETA UMD.	BETA UMD. t-value	R2
Average	**-1.396**	**-1.649**	**-1.462**	**0.197**	**-2.177**	**0.197**	**0.430**	**0.995**	**-49.294**	**-3.058**	**9.412**	**0.390**	**-32.093**	**-2.028**	**0.469**
SD	**1.067**	**1.251**	**1.037**	**0.000**	**1.160**	**0.000**	**0.514**	**2.112**	**27.400**	**1.172**	**17.966**	**0.559**	**21.319**	**0.779**	**0.121**
Median	**-1.301**	**-1.811**	**-1.340**	**0.197**	**-2.030**	**0.197**	**0.398**	**0.749**	**-61.326**	**-2.932**	**4.770**	**0.312**	**-28.991**	**-2.210**	**0.522**
Min	-3.987	-3.491	-3.987	0.197	-3.987	0.197	-0.592	-1.978	-85.648	-4.932	-34.669	-0.776	-76.777	-3.453	0.256
p25	-1.714	-2.176	-1.761	0.197	-2.944	0.197	0.268	0.181	-72.572	-3.930	2.540	0.087	-44.081	-2.609	0.351
p50	-1.301	-1.811	-1.340	0.197	-2.030	0.197	0.398	0.749	-61.326	-2.932	4.770	0.312	-28.991	-2.210	0.522
p75	-0.619	-1.115	-0.637	0.197	-1.375	0.197	0.685	1.090	-18.582	-2.178	13.865	0.504	-13.793	-1.535	0.559
p90	-0.259	-0.840	-0.345	0.197	-1.031	0.197	1.110	2.343	-12.258	-1.581	35.030	1.271	-7.232	-0.906	0.604
Max	0.197	2.860	-0.024	0.197	-0.277	0.197	1.408	9.877	-1.967	-0.798	51.973	1.581	-2.604	-0.652	0.668
Count	25	25	24	1	10	1	25	25	25	25	25	25	25	25	25

Panel A, Panel B, Panel C, and Panel D of Table 19 show the results obtained from the cross-sectional performance analysis employing the method of Selection Return and Regressing returns employing the customized benchmarks based on Sharpe weights, the customized benchmarks based on the portfolio-based style, and the results obtained from the Carhart four factors model. The results correspond to performance evaluation for the entire sample of funds investigated. In Panel A, first group of columns in the table shows the mean difference, standard deviation, t-statistic for Selection results, positives and negatives alphas and the significant alpha at the level of 5%. In Panel B, first and second group of columns in the table shows the alpha, t-statistic for alpha results, positives and negatives alphas, the significant alpha at the level of 5%, beta of the variable (style customized benchmark Sharpe), and $\boldsymbol{R^2}$ that results from the application of the regression analysis in equation (15). The second group of columns in Panel B shows the rolling regression of monthly fund risk-adjusted performance estimates. This rolling regression yields a total of 6,980 monthly risk-adjusted returns. In Panel C, first and second group of columns in the table shows the alpha, t-statistic for alpha results, positives and negatives alphas, the significant alpha at the level of 5%, beta of the variable (style customized benchmark by Prospectus), and $\boldsymbol{R^2}$ that results from the application of the regression analysis in equation (16). The second group of columns in Panel C shows the rolling regression of monthly fund risk-adjusted performance estimates. This rolling regression yields a total of 6,980 monthly risk-adjusted returns. In Panel D, first and second group of columns in the table shows the alpha, t-statistic for alpha results, positives and negatives alphas, the significant alpha at the level of 5%, beta of the four factors (Carhart model), and $\boldsymbol{R^2}$ that results from the application of the regression analysis in equation (17). The results contained in this panel are only for equity funds. The second group of columns in Panel D shows the rolling regression of monthly fund risk-adjusted performance estimates. This rolling regression yields a total of 802 monthly risk-adjusted returns, for equity investment funds.

Note that, on average, the performance results are consistent among the selection return model (Panel A), the customized benchmark return based on Sharpe weights (Panel B), and the approximated benchmark return based on the style in the prospectus (Panel C). Also notice that the average fund return before fees is 0.294% per month (see Table 8).

If we observe in Panel A of Table 19 the mean difference (selection return), we notice that, on average, all funds underperformed their style benchmark by –0.021% per month, with an average standard deviation of 0.31% per month. However, the average t-statistic associated with the mean difference was small in absolute value, suggesting that the average difference was apparently not statistically significantly different from zero. On average, the selection return is negative, resulting in a negative total alpha from June 2009 through December 2015 for all investment funds. However, if we observe the positive and negatives alphas in columns 5 and 6 of Panel A, we realize that more than 65% of the funds (120 out of 183 funds) underperformed the style benchmark by an average of –0.141% per month, and 35% of the funds (63 out of 183 funds) overperformed the style benchmark by an average of 0.21% per month. The underperformed results are supported by a high t-statistic because more than 71% of these negative alphas (column 7: 86 out of 120 funds) are significant at the 5% level. Thus, conclusive evidence exists that the activity in 47% of investment funds in Colombia have underperformed a passive benchmark.

This result is also consistent when we regress the monthly returns with the customized benchmark by fund based on the Sharpe weights (Equation 15) and with the approximated benchmark based on the style in the prospectus (Equation 16). Panels B and C in Table 19 (columns grouped by a single beta estimation) show an average alpha that is also negative when compared with the customized benchmark calculated in Equations (15) and (16). In both cases, the results are negative total alphas of –0.015% and –0.113% per month, respectively, during the historical period of all investment funds. These results are supported by $\boldsymbol{R^2}$ of 88% and 55%, respectively. However, the average t-statistics associated with the alpha is small in absolute value for both cases, suggesting apparently that the average difference was not statistically significantly different from zero. However, if positive and negatives alphas are observed in columns 4 and 5 of Panels B and C, then more than 66% and 80% of the funds, respectively, underperformed their style benchmarks by –0.135% and –0.193%, respectively, per month. Moreover, 34% and 20% of the funds, respectively, overperformed their style benchmarks by an average of 0.22% and 0.21%, respectively, per month.

In the regression model using the customized benchmark under the Sharpe weights (Equation 15), 70% of the underperformed results (84 out of 121 funds; column 6 Panel B) are supported by significant t-statistics at least at the 5% level. This result is consistent with the selection return. In the regression model using the customized benchmark based on the portfolio-based style in the prospectus (Equation 16), the underperformed results are also supported by a high t-statistic but at a lower proportion. That is, 43% of the underperformed results (64 out of 147 funds; column 6 Panel C) are significant at the 5% level. Thus, conclusive evidence exists that funds in more than 43% of investment funds in Colombia have underperformed a passive benchmark.

The results are also very consistent for the rolling regressions using the customized benchmarks based on the Sharpe weights and the portfolio style in the prospectus. Panels B and C in Table 19 (columns grouped by rolling beta estimation) show that the average alpha is also negative. In both cases, the results are negative total alphas of –0.027% and –0.099% per month, respectively. These results are supported by an $\boldsymbol{R^2}$ of 88% and 54%, respectively. If we observe positive and negatives alphas in columns 13 and 14 of Panels B and C, a similar result is noticed: more than 66% and 71% of the funds, respectively, underperformed their style benchmarks by –0.027% and –0.099%, respectively, per month. This result is also supported by a high t-statistic, and more than 45% and 36% of these negative alphas, respectively, are significant at the 5% level.

These results are even worse when we regress only the monthly returns of equity funds using the four-factors model in Equation (17) (Carhart, 1997). Panel D in Table 19 (columns grouped by single beta and rolling beta estimation) shows that, on average, the alpha is negative. The results are negative total alphas of –0.785% (column 2) and –1.396% (column 17) per month, respectively. These results are supported by a $\boldsymbol{R^2}$ of 36% and 47%, respectively. If we observe positive and negative alphas in columns 4, 5, 19, and 20 of Panel D, we notice that more than 90% of equity funds underperformed their benchmarks by –0.935% and –1.462%, respectively, per month. Moreover, 10% of equity funds overperformed their benchmarks by 0.32% and 0.2%, respectively, per month. The underperformed results are also supported by a high t-statistic because more than 68% and 42%, respectively, of these negative alphas (15 out of 22 equity funds, column 6; and 10 out of 24 equity funds, column 21) are significant at the

5% level. However, the overperformed results are not supported by a high t-statistic (columns 7 and 22) because only one out of 24 equity funds reflects a high t-statistic. Thus, conclusive evidence exists that equity funds in Colombia underperform after adjusting for standard systematic risk factors.

The results we have obtained are roughly consistent with the hypothesis that average investment funds (mutual funds) cannot “beat the market” before costs because such funds constitute a large (and presumably representative) part of the market (Sharpe, 1992).

In addition, these results are consistent with previous research. We found that fund styles in Colombia generally do not deviate from the customized benchmark, and this benchmark is closely aligned with a fund’s style. Viewed in this light, not completely surprising is that historically few investment funds overperformed market benchmarks but, rather, exhibited an insignificant positive alpha. Similar results were found for mutual funds in the U.S. market (Ippolito, 1989; Sharpe, 1992; Elton et al., 1993; Malkiel, 1995; Chen et al., 2002).

Figures 18 and 19 show the results of the average alphas and their t-statistics obtained by applying this type of analysis for all investment funds, that is, the mean difference (selection return) and alpha obtained by regressing the monthly return with the customized benchmarks and the Carhart four-factor model. These figures emphasize the previous results because, on average, the total alpha from June 2009 through December 2015 for all investment funds has been similar.

Figure 18: Comparison between mean of Selection Return results and Alphas arisen from regressing monthly return risk adjusted with benchmark of portfolio weights and benchmark on prospectus – from June 2009 to December 2015

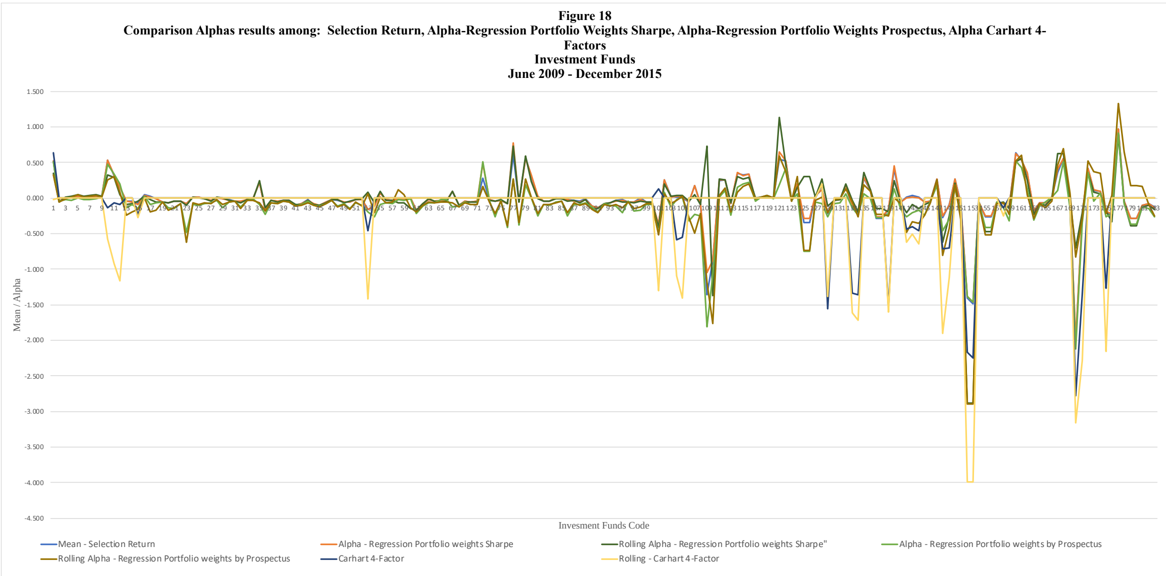
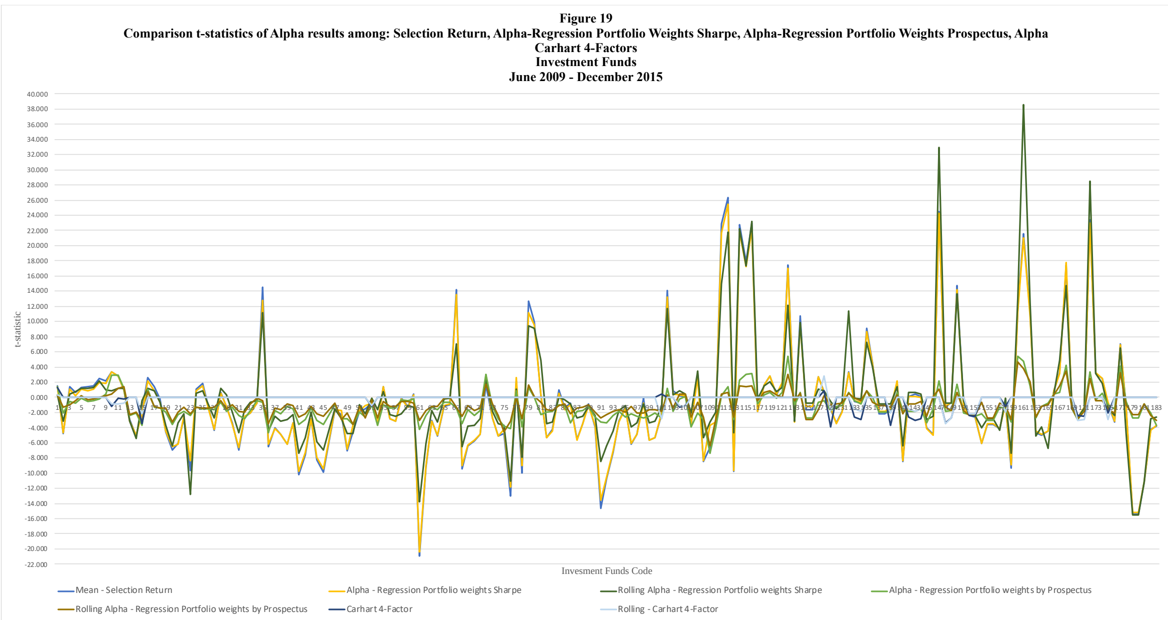


Figure 19: Comparison between t-statistics of Alphas results among Selection Return, Alpha-Regression Portfolio Weights Sharpe, Alpha-Regression Portfolio Weights Prospectus, Alpha Carhart 4-Factors – from June 2009 to December 2015



As we may see, small differences in performance results exist between the alphas obtained using the customized benchmarks based on the Sharpe weights (Equation 15) and the alphas obtained using the customized benchmarks based on prospectuses (Equation 16). The underperforming funds are higher when we regress the monthly returns with the customized benchmarks based on the prospectuses (in Panel B, 147 funds in column 5 and 130 funds in column 14) than those based on the Sharpe weights (in Panel A, 121 funds in column 5 and 122 funds in column 14). Thus, no conclusive evidence exists that advisory companies in Colombia are interested in intentionally manipulating prospectuses or technical reports to present higher alphas to investors to ensure that they infer that management activities have resulted in more value added over a passive benchmark.

As Figure 16 indicates, the correlation between the customized benchmarks based on the Sharpe weights and the fund returns are higher than the correlation between the customized benchmarks based on the prospectuses and fund returns. This result is consistent with the tracking error between monthly fund returns and the customized benchmark based on the Sharpe weights and the tracking error between monthly fund returns and the customized benchmark based on the prospectuses. The benchmark that minimizes the tracking error allows us to infer how close the fund's exposures are to variations in the asset class returns during the period studied (Sharpe, 1992).

Figure 20: Tracking Error (TEV) between monthly fund´s return and the customized benchmark based on Sharpe weights and tracking error between monthly fund´s return and the customized benchmark based on Prospectus.

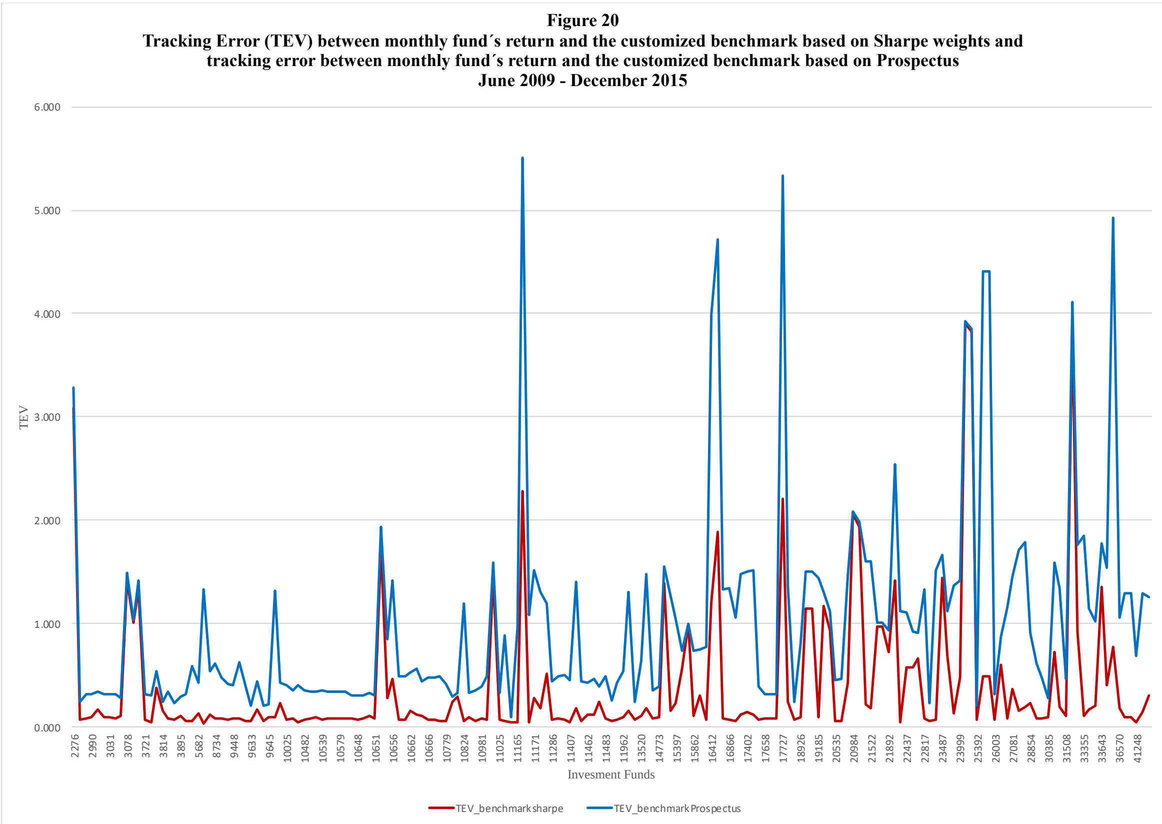


Figure 20 and Table 20 show the average tracking errors obtained from the style analysis based on the customized benchmark using the Sharpe weights and the style analysis based on the approximated benchmark using the prospectus weights for all investment funds during the sample period. As is observed in Figure 20 and Table 20, the benchmark returns that minimize the tracking error or the fund's exposures to return variations is the benchmark based on the Sharpe weights. Thus, this result emphasizes and supports the need for a customized benchmark return based on the Sharpe weights to evaluate fund performance. This customized benchmark return is needed because the customize benchmark return based on the prospectus has a higher tracking error (average 1.027% monthly) than the tracking error of the customize benchmark return based on the Sharpe weights (average 0.395% monthly). Therefore, the style fund classifications provided by the advisory companies in their technical reports might not be as precise as investors require, and they are noisier than the customized benchmark determined using the Sharpe weights. This result is approximately consistent with our hypothesis that investors in Colombia do not have enough accurate and timely information to evaluate fund performance in the Colombian market.

Table 20: Summary Statistics - Tracking Error (TEV) between monthly fund´s return and the customized benchmark based on Sharpe weights and tracking error between monthly fund´s return and the approximated benchmark based on Prospectus.

Summary Statistics	Dif_Return_Benchmark_ Sharpe	TEV_Benchmark_ Sharpe	Dif_Return_Benchmark_ Prospectus	TEV_Benchmark_ Prospectus
Average	**-0.021**	**0.395**	**-0.109**	**1.027**
SD	**0.314**	**0.676**	**0.362**	**1.006**
Min	-2.013	0.041	-1.658	0.095
p25	-0.071	0.079	-0.183	0.355
p50	-0.031	0.102	-0.119	0.624
p75	0.021	0.308	-0.060	1.347
Max	0.973	3.902	2.354	5.509

This table shows the result of the tracking error between monthly fund´s return and the customized benchmark based on Sharpe weights and tracking error between monthly fund´s return and the approximated benchmark based on Prospectus. The benchmark that minimizes the tracking error allow us to infer how close are the fund's exposures to variations in the returns of the asset classes during the period studied (Sharpe, 1992). This table emphasize and support the need we had to customize the benchmark return based on Sharpe weights for evaluating fund performance, because the customize benchmark return based on Prospectus has a higher tracking error (1.027% monthly in average) than the tracking error of the customize benchmark return based on Sharpe weights (0.395% monthly in average), meaning that the style fund classifications provided by the advisory companies in their technical reports, might not be as precise as the investors need and they are noisier than the customized benchmark we determined based on Sharpe weights.

The approach that we employed to analyze fund performance under these different benchmarks has provided us with important insights into how investment funds in the Colombian markets have performed during the sample period. Now, we classify the investment fund performance based on our empirical style classification determined in chapter 4 to understand this performance given different investment objectives. Table 21 reports the results obtained by classifying the investment fund performance into the five categories of investment funds determined in a previous chapter. Appendix 7 provides greater detail on fund performance results from the employment of all of the methods described in the preceding paragraphs.

In Category 1 of Table 21, we notice that all funds classified under this category underperformed, on average, both the style benchmark based on the Sharpe weights by –0.436% and the style benchmark based on the prospectuses by –0.476% per month (columns 4 and 11 of Table 21), with an average $\boldsymbol{R^2}$ of 79% and 78%, respectively. For both benchmarks, the average standard deviation was approximately 1% per month. However, a deeper review into the analysis through a review of the positive and negative alphas for all investment funds (columns 6 and 7 of Table 21) shows that 60% of the funds (nine out of 15 funds) underperformed the style benchmark based on Sharpe by –0.821% per month, whereas 40% of the funds slightly overperformed this style benchmark by 0.141% per month. The t-statistics associated with this result indicated that 33% (three out of nine funds) of the underperforming funds are statistically significant at a 5% level. The t-statistics associated with the overperforming funds is small in absolute value, suggesting that the average alpha is not statistically significantly different from zero. This result is also supported by regressing the monthly return with the customized benchmarks based on the prospectuses. In this category, 66% of the funds also underperformed this style benchmark (see columns 13 and 14) by –0.793% per month, whereas 34% of the funds slightly overperformed this style benchmark by 0.159%. The t-statistics associated with this result is very similar: 30% (three out of 10 funds) of the underperforming funds are statistically significant at the 5% level, whereas the t-statistics associated with the overperforming funds are not statistically significantly different from zero. This result is also supported by the selection return method (for further reference, see Appendix 7).

In this category (equity funds), considering that the performance results using the benchmark based on the prospectuses do not differ significantly with the performance results using our customized benchmark based on Sharpe, conclusive evidence exists that argues that advisory companies are intentionally not manipulating the information in the technical reports to alter their management activates and distort fund performance under this category. Thus, investors might be well informed regarding their investments in equity assets to evaluate fund performance.

Table 21: Average Statistics and t-test, grouped by Empirical Style Classification Algorithm: Rolling regression results using the two customized benchmarks by Sharpe and Prospectus, and Carhart 4-Factor model (Only for Equity Funds: Category 1).

ALPHA USING SHARPE BENCHMARK — ROLLING BETA ESTIMATION

SUMMARY STATISTICS	CLUSTER SHARPE	#OBS.	ALPHA_ESTIMATED	ALPHA_ESTIMATED t-value	ALPHA<0	ALPHA>0	Significant at 5% ALPHA<0	Significant at 5% ALPHA>0	R2
Category 1									
Average		**55.7**	**-0.436**	**-0.552**	**-0.821**	**0.141**	**-2.156**	**0.000**	**0.785**
SD		**16.2**	**0.988**	**1.248**	**1.116**	**0.126**	**1.027**	**0.000**	**0.188**
Median		53.0	-0.107	-0.256	-0.197	0.069	-2.882	0.000	0.888
Min		33.0	-2.882	-2.693	-2.882	0.036	-2.882	0.000	0.437
p25		45.0	-0.201	-1.430	-0.704	0.042	-2.882	0.000	0.635
p50		53.0	-0.107	-0.256	-0.197	0.069	-2.882	0.000	0.888
p75		70.0	0.045	0.347	-0.181	0.238	-1.793	0.000	0.935
p90		79.4	0.208	1.060	-0.093	0.316	-1.140	0.000	0.956
Max		81.0	0.345	1.210	-0.036	0.345	-0.704	0.000	0.977
Count		15	15	15	9	6	3	0	15
Category 2									
Average		**62.8**	**0.025**	**0.084**	**-0.078**	**0.242**	**-0.078**	**0.291**	**0.945**
SD		**18.8**	**0.223**	**8.362**	**0.090**	**0.262**	**0.137**	**0.194**	**0.135**
Median		67.5	-0.034	-2.083	-0.055	0.203	-0.062	0.262	0.984
Min		24.0	-0.471	-15.532	-0.471	0.003	-0.471	0.035	0.196
p25		47.0	-0.066	-3.675	-0.080	0.032	-0.087	0.194	0.972
p50		67.5	-0.034	-2.083	-0.055	0.203	-0.062	0.262	0.984
p75		81.0	0.022	1.108	-0.033	0.298	-0.046	0.360	0.990
p90		81.0	0.265	11.553	-0.018	0.614	-0.032	0.538	0.994
Max		81.0	1.134	38.596	-0.005	1.134	0.727	0.892	0.999
Count		134	134	134	91	43	69	25	134
Category 3									
Average		**62.9**	**-0.019**	**0.046**	**-0.193**	**0.223**	**-0.356**	**0.289**	**0.717**
SD		**19.4**	**0.354**	**3.111**	**0.331**	**0.216**	**0.454**	**0.264**	**0.227**
Median		70.5	-0.044	-0.777	-0.119	0.128	-0.155	0.157	0.769
Min		25.0	-1.368	-5.151	-1.368	0.020	-1.368	-0.003	0.156
p25		50.8	-0.141	-1.738	-0.147	0.043	-0.208	0.079	0.576
p50		70.5	-0.044	-0.777	-0.119	0.128	-0.155	0.157	0.769
p75		81.0	0.084	1.039	-0.051	0.305	-0.141	0.590	0.914
p90		81.0	0.305	4.321	-0.044	0.593	-0.119	0.608	0.936
Max		81.0	0.620	9.432	-0.003	0.620	-0.099	0.620	0.960
Count		24	24	24	14	10	6	5	24
Category 4									
Average		**48.9**	**-0.075**	**0.177**	**-0.131**	**0.264**	**0.000**	**0.000**	**0.546**
SD		**14.3**	**0.156**	**0.599**	**0.078**	**0.000**	**0.000**	**0.000**	**0.108**
Median		46.0	-0.084	0.454	-0.114	0.264	0.000	0.000	0.611
Min		26.0	-0.256	-0.785	-0.256	0.264	0.000	0.000	0.376
p25		43.5	-0.174	-0.316	-0.189	0.264	0.000	0.000	0.464
p50		46.0	-0.084	0.454	-0.114	0.264	0.000	0.000	0.611
p75		53.0	-0.049	0.653	-0.058	0.264	0.000	0.000	0.631
p90		63.2	0.076	0.770	-0.049	0.264	0.000	0.000	0.646
Max		77.0	0.264	0.893	-0.049	0.264	0.000	0.000	0.648
Count		7	7	7	6	1	0	0	7
Category 5									
Average		**66.3**	**-0.237**	**-0.401**	**-0.517**	**0.322**	**0.000**	**0.000**	**0.706**
SD		**13.7**	**0.405**	**0.894**	**0.105**	**0.000**	**0.000**	**0.000**	**0.073**
Median		70.0	-0.413	-0.722	-0.517	0.322	0.000	0.000	0.661
Min		48.0	-0.622	-1.300	-0.622	0.322	0.000	0.000	0.648
p25		59.0	-0.517	-1.011	-0.570	0.322	0.000	0.000	0.655
p50		70.0	-0.413	-0.722	-0.517	0.322	0.000	0.000	0.661
p75		75.5	-0.045	0.048	-0.465	0.322	0.000	0.000	0.735
p90		78.8	0.175	0.510	-0.434	0.322	0.000	0.000	0.779
Max		81.0	0.322	0.818	-0.413	0.322	0.000	0.000	0.808
Count		3	3	3	2	1	0	0	3

ALPHA USING BENCHMARK FROM PROSPECTUS — ROLLING BETA ESTIMATION

SUMMARY STATISTICS	ALPHA_ESTIMATED	ALPHA_ESTIMATED t-value	ALPHA<0	ALPHA>0	Significant at 5% ALPHA<0	Significant at 5% ALPHA>0	R2
Category 1							
Average	**-0.476**	**-0.714**	**-0.793**	**0.159**	**-2.205**	**0.000**	**0.776**
SD	**0.985**	**1.293**	**1.071**	**0.128**	**0.975**	**0.000**	**0.190**
Median	-0.206	-0.459	-0.259	0.081	-2.894	0.000	0.864
Min	-2.895	-2.866	-2.895	0.030	-2.895	0.000	0.423
p25	-0.278	-1.744	-0.692	0.055	-2.895	0.000	0.631
p50	-0.206	-0.459	-0.259	0.081	-2.894	0.000	0.864
p75	0.043	0.321	-0.208	0.299	-1.860	0.000	0.932
p90	0.212	0.907	-0.051	0.316	-1.239	0.000	0.951
Max	0.328	1.358	-0.033	0.328	-0.826	0.000	0.974
Count	15	15	10	5	3	0	15
Category 2							
Average	**-0.028**	**-1.030**	**-0.134**	**0.220**	**-0.209**	**0.586**	**0.563**
SD	**0.254**	**1.562**	**0.157**	**0.265**	**0.239**	**0.361**	**0.285**
Median	-0.063	-1.234	-0.084	0.139	-0.157	0.526	0.586
Min	-1.190	-6.374	-1.190	0.004	-1.190	0.051	0.002
p25	-0.106	-1.975	-0.146	0.041	-0.234	0.446	0.324
p50	-0.063	-1.234	-0.084	0.139	-0.157	0.526	0.586
p75	0.020	-0.431	-0.061	0.275	-0.103	0.649	0.823
p90	0.184	0.665	-0.039	0.597	-0.049	0.953	0.918
Max	1.335	4.677	-0.006	1.335	0.178	1.335	0.994
Count	134	134	94	40	33	7	134
Category 3							
Average	**-0.180**	**-1.198**	**-0.311**	**0.215**	**-0.459**	**0.000**	**0.320**
SD	**0.425**	**1.568**	**0.402**	**0.172**	**0.485**	**0.000**	**0.310**
Median	-0.146	-1.262	-0.207	0.216	-0.231	0.000	0.219
Min	-1.759	-3.447	-1.759	0.010	-1.759	0.000	0.011
p25	-0.226	-2.660	-0.247	0.049	-0.621	0.000	0.051
p50	-0.146	-1.262	-0.207	0.216	-0.231	0.000	0.219
p75	0.001	-0.073	-0.105	0.347	-0.190	0.000	0.587
p90	0.237	1.272	-0.056	0.419	-0.131	0.000	0.843
Max	0.466	1.748	-0.001	0.466	-0.095	0.000	0.871
Count	24	24	18	6	10	0	24
Category 4							
Average	**-0.256**	**-1.160**	**-0.301**	**0.009**	**-0.163**	**0.000**	**0.381**
SD	**0.172**	**1.005**	**0.145**	**0.000**	**0.000**	**0.000**	**0.180**
Median	-0.330	-0.910	-0.340	0.009	-0.163	0.000	0.374
Min	-0.476	-3.203	-0.476	0.009	-0.163	0.000	0.159
p25	-0.387	-1.422	-0.405	0.009	-0.163	0.000	0.269
p50	-0.330	-0.910	-0.340	0.009	-0.163	0.000	0.374
p75	-0.112	-0.710	-0.205	0.009	-0.163	0.000	0.424
p90	-0.033	-0.252	-0.112	0.009	-0.163	0.000	0.580
Max	0.009	0.257	-0.061	0.009	-0.163	0.000	0.749
Count	7	7	6	1	1	0	7
Category 5							
Average	**-0.352**	**-0.931**	**-0.657**	**0.258**	**0.000**	**0.000**	**0.617**
SD	**0.448**	**0.975**	**0.146**	**0.000**	**0.000**	**0.000**	**0.138**
Median	-0.511	-1.334	-0.657	0.258	0.000	0.000	0.524
Min	-0.804	-1.872	-0.804	0.258	0.000	0.000	0.514
p25	-0.657	-1.603	-0.731	0.258	0.000	0.000	0.519
p50	-0.511	-1.334	-0.657	0.258	0.000	0.000	0.524
p75	-0.127	-0.461	-0.584	0.258	0.000	0.000	0.668
p90	0.104	0.063	-0.540	0.258	0.000	0.000	0.755
Max	0.258	0.413	-0.511	0.258	0.000	0.000	0.812
Count	3	3	2	1	0	0	3

ALPHA USING CARHART 4-FACTOR MODEL (only equity funds) — ROLLING BETA ESTIMATION

SUMMARY STATISTICS	ALPHA_ESTIMATED	ALPHA_ESTIMATED t-value	ALPHA<0	ALPHA>0	Significant at 5% ALPHA<0	Significant at 5% ALPHA>0	BETA Market	BETA Market t-value	BETA SMB	BETA SMB t-value	BETA HML	BETA HML t-value	BETA UMD.	BETA UMD. t-value	R2
Category 1															
Average	**-1.861**	**-1.677**	**-1.861**	**0.000**	**-2.863**	**0.000**	**0.438**	**0.512**	**-69.908**	**-3.594**	**12.048**	**0.344**	**-45.838**	**-2.330**	**0.509**
SD	**1.069**	**0.894**	**1.069**	**0.000**	**0.918**	**0.000**	**0.563**	**0.715**	**10.340**	**1.080**	**22.576**	**0.633**	**16.086**	**0.681**	**0.117**
Median	-1.596	-1.767	-1.596	0.000	-2.724	0.000	0.405	0.479	-69.843	-3.903	9.544	0.283	-43.615	-2.496	0.534
Min	-3.987	-3.072	-3.987	0.000	-3.987	0.000	-0.592	-0.536	-85.648	-4.932	-34.669	-0.776	-76.777	-3.453	0.256
p25	-2.220	-2.173	-2.220	0.000	-3.781	0.000	0.200	0.087	-77.292	-4.356	0.847	0.032	-50.916	-2.738	0.457
p50	-1.596	-1.767	-1.596	0.000	-2.724	0.000	0.405	0.479	-69.843	-3.903	9.544	0.283	-43.615	-2.496	0.534
p75	-1.273	-1.106	-1.273	0.000	-2.188	0.000	0.676	0.776	-63.249	-2.862	24.650	0.648	-34.172	-1.878	0.583
p90	-0.987	-0.843	-0.987	0.000	-1.876	0.000	1.253	1.493	-57.233	-2.056	44.560	1.271	-26.161	-1.484	0.629
Max	-0.024	0.318	-0.024	0.000	-1.596	0.000	1.408	2.072	-47.054	-1.405	51.973	1.581	-23.723	-0.903	0.668
Count	15	15	15	0	6	0	15	15	15	15	15	15	15	15	15

This Table shows the results obtained by classifying the performance of investment funds into the five categories of investment funds we have determined in section 4.3.4.2. The results correspond to performance evaluation for the entire sample of funds investigated and classified by the empirical style category. This empirical style category is the maximum likelihood method described in Appendix 5. A likelihood ratio suggested by Brown and Goetzmann (1997) shows that the cross-section of investment fund returns is driven by at least six separate factors. The results are the summary statistics of the rolling regression using the two customized benchmarks (by Sharpe and Prospectus) and Carhart 4-factors model, grouped by Empirical Style Classification. We show alpha, t-statistic for alpha results, positives and negatives alphas, the significant alpha at the level of 5% and R^2 that results from the application of the regressions analysis.

If we analyze the regression results using the 4-factor model factors (columns 18 and 20 of Table 21) (Carhart, 1997), we still notice that all funds classified under category 1 (equity funds) underperformed, on average. However, the underperforming result of –1.861% with an R^2 of 51% is almost four times as negative when compared with the other two customized benchmarks previously mentioned. The average standard deviation is approximately 1.1% per month. The t-statistics associated with this result show that 40% (six out of 15 funds) of the underperforming funds are statistically significant at the 5% level. The other interesting results are the loadings on the size, book-to-market, and momentum factors. The loadings on the size and momentum factors are always negative, whereas the loading on book-to-market is primarily positive. The existence of this negative relationship between performance and size and momentum and the positive relationship between performance and book-to-market might be explained because these funds follow investment strategies in high-value or large companies instead of momentum or small companies. This result is consistent with the average loadings obtained by Ferreira et al. (2012) in an analysis of Indonesia. However, Chen et al. (2004) found different results in the U.S. market—they showed that increases in fund size lead to declines in fund performance.

In Category 2, we found differences between the performance results using the customized benchmark from the Sharpe weights and the benchmark from the prospectuses. We notice that, on average, all funds classified under this category overperformed the passive benchmark based on the Sharpe weights, obtaining a small positive alpha of 0.025% per month (column 3) with an average R^2 of 95%. The average standard deviation is also very small, at 0.22% per month. However, when we observe the regression results using the benchmark return based on the prospectus, we notice a different result. On average, all funds underperformed this style benchmark by –0.028% (column 11), with an average $\boldsymbol{R^2}$ of 56%. The average standard deviation was also very small, at 0.25% per month. Now, if we look the negatives and positives alphas for all investment funds for this category under these two regression models (columns 6–7 and 13–14 of Table 21), we notice a similar result in the number of funds that underperformed (between 91 and 94 funds, or 68%–70% of funds with negative alphas) and over-performed (between 43 and 40 funds, or 32%–30% of funds with positive alphas) both style benchmarks but a different outcome in the performing results. The underperformance results for funds in category 2 using the benchmark Sharpe weights were very small, –0.078%, with an average standard deviation of 0.09%. Moreover, 76% of the funds (69 out of 91 funds, column 14) are statistically significant at the 5% level. Using the benchmark from the prospectus, the underperformance results for funds in category 2 were slightly worse, by –0.13%, with a higher average standard deviation of 0.16% and a lower proportion of 35% of the funds (33 out of 94 funds, column 15) are statistically significant at a 5% level. The results for the overperforming funds under these two models show similar results, averages of 0.24% and 0.22%. However, the t-statistics associated with this result were much lower for the regression model under the prospectus benchmark than the Sharpe benchmark (see columns 9 and 16).

In Category 3, the performance results are still not similar under these two regression models. The regression model using the benchmark based on the Sharpe weights (first group of columns) shows that, on average, all funds in this category underperformed its style benchmarks by –0.019% (column 4) with an R^2 of 72% and an average standard deviation of 0.35% per month. However, looking only at the negative alphas, we notice that 58% of funds (14 out of 24 funds) underperformed the style benchmark by –0.19% per month, whereas 42% of the funds overperformed (10 out of 24 funds) this style benchmark by 0.22% per month. The t-statistics associated with this result show that 43% (6 out of 14 funds) of the underperforming funds are statistically significant at a 5% level, and 50% (5 out of 10 funds) of the overperforming funds are statistically significant at a 5% level. The regression model using benchmarks based on prospectuses (second group of columns) shows higher negatives results. On average, all funds in this category underperformed their style benchmarks by –0.18% (column 11) with a lower R^2 of 32% and average standard deviation of 0.43% per month. Looking only at the negative alphas, we notice that a much higher number of funds relative to the previous regression model underperformed the style benchmark (75% of funds: 18 out of 24 funds) by –0.31% per month, whereas only 25% of the funds overperformed (6 out of 24 funds) this style benchmark by 0.21% per month. The t-statistics associated with this result show that 55% (10 out of 18 funds) of the underperforming funds are statistically significant at a 5% level, and the rest of the funds are not statistically significant.

The results obtained for funds classified in Categories 2 and 3 support the argument that no conclusive evidence exists to show that advisory companies in Colombia are intentionally interested in manipulating the prospectuses or technical reports to present higher alphas that result in more value added over a passive benchmark. However, and bearing in mind that funds classified in category

2 represent more than two-thirds of the investment funds in Colombia, we might argue that the information in the technical reports for these two categories is not precise and is noisier. Thus, these results obviously emphasize the need to customize a more robust benchmark based on the Sharpe weights for evaluating fund performance because this benchmark best explains fund exposure to variations in the returns of the asset classes during the period studied.

In Category 4, we notice results similar to those of Category 3. Funds in this category provided, on average, a higher underperforming result using the benchmark based on prospectuses (–0.26% per month) than using the benchmark based on Sharpe (–0.075% per month). The average standard deviation is roughly similar (0.17% per month for the benchmark based on prospectuses, and 0.15% per month for the benchmark based on Sharpe weights). However, the $\boldsymbol{R^2}$ for funds using the benchmark based on Sharpe is higher (55%) than the $\boldsymbol{R^2}$ for funds using the benchmark based on prospectuses (38%). The absolute values of the t-statistics associated with these results from the two regression models were not statistically significantly different from zero.

Funds classified in Category 5 present no significant differences in the performance results between the two regression models using the benchmark based on Sharpe and the benchmark based on prospectuses. We notice that, on average, funds in this category underperformed their style benchmark by –0.24% and –0.35% per month, respectively, with an $\boldsymbol{R^2}$ of 71% and 62% and an average standard deviation of 0.40% and 0.45% per month, respectively. For the two regression models, 67% of the total funds (2 out of 3 funds) underperformed their style benchmark by –0.40% and –0.66%, respectively, whereas 33% of the funds overperformed the style benchmark by 0.32% and 0.26% per month, respectively. The absolute value of the t-statistics associated with these results from the two regression models was not statistically significantly different from zero.

6.3. Interpretations

To summarize our results, we find that fund styles in Colombia generally do not deviate from a widely followed benchmark, and the customized benchmark based on the Sharpe weights is closely aligned with the fund's style. In addition, funds seemed averse to strategies involving the deep value of stock or equity because, as we have described, more than 90% of the investment funds invested in Colombia follows the money market's passive benchmarks. Viewed in this light, not completely surprising is that, historically, most investment funds have underperformed the style benchmark (66% of the funds investigated; see Table 19), and some have outperformed market benchmarks (44%; see Table 19) but provided an insignificant positive alpha. Similar findings have been made about mutual funds in the U.S. market (Ippolito, 1989; Sharpe, 1992; Elton et al., 1993; Malkiel, 1995; Chen et al., 2002; Ferreira et al., 2012).

Our results show that no conclusive evidence exists to argue that advisory companies in Colombia are interested in intentionally manipulating the prospectuses or technical reports to present higher alphas that result in more value added over a passive benchmark.

Our findings also emphasize and support the need to have constructed—as a valuable supplement to other methods designed—a more robust benchmark return based on the Sharpe weights for evaluating fund performance because doing so can provide a consistent view of investment decisions that investors make (Sharpe, 1992). The customize benchmark return based on prospectuses is less correlated with fund returns because the style fund classifications provided by the advisory companies in their technical reports might not be as precise as the investors need, and they are noisier. This result is consistent with our hypothesis that investors in Colombia do not have enough, accurate, and timely information to evaluate fund performance in the Colombian market.

Our results are also consistent with the self-interest from the manager's perspective because, as Chan et al. (2002) pointed out, more scope exists for money managers to follow their self-interests, which have adverse consequences for portfolio performance. Thus, the key finding in this section is that the manager or company advisor plays an important role in the investment fund industry in Colombia, and the evidence for nonperforming results persists.

In addition, several reasons may explain why investment funds managers in Colombia have some preference for money market assets—investments in this type of asset generally show good past returns, and a tilt toward these assets may appear to be safe from the standpoint of personal career risk. However, not completely surprising is that some managers favor other strategy styles, such as equity or stocks with strong past performances. Chen et al. (2002) pointed out that value strategies take a long time to become profitable, whereas the money market style strategy and past winners at least have price momentum working in their favor over the intermediate term.

Another explanation for the Colombian investment fund's tendency, which should be consistent with the theory (see Chen et al. (2002)), is that managers or company advisors follow strategies that cannot be easily summarized by a single characteristic, such as equity, money market, or past returns. Instead, managers or advisory companies may focus on many other security characteristics such that the result is a portfolio that does not deviate too much from a diversified benchmark index. Also possible is that managers or advisory companies realize that superior long-term results are unachievable or entail a higher risk in an efficient or illiquid market; hence, many do not deviate markedly from benchmarks.

7. RELATIONSHIP BETWEEN FEES AND PERFORMANCE

After having measured the risk-adjusted returns of investment funds before expenses, in this section, we investigate the link between compensation fees and risk-adjusted returns for Colombian investment funds from 2009 to 2015.

The theory predicts that investment funds fees in a well-functioning market and in the absence of market friction should be positively correlated with the expected risk-adjusted returns before expenses and should have, in equilibrium, zero expected risk-adjusted return after expenses (Berk and Green, 2004; Gil-Bazo et al., 2009).

Gil-Bazo et al. (2009: page 2159) stated that, in this context, if investors know a fund's alphas ($\boldsymbol{Y_i}$), then equilibrium requires that $\boldsymbol{Y_i - Fee_i = 0}$ for every fund *i,* where $\boldsymbol{Fee_i}$ corresponds to the fund's compensation fee. Thus, the equilibrium as they stated can be rewritten as $\boldsymbol{Y_i = Fee_i}$ for every fund *i.* If investors do not know funds' alphas, $\boldsymbol{Y_i}$, the $\boldsymbol{Y_i}$ under the equilibrium condition of Berk and Green (2004) is replaced with the expected risk-adjusted returns, and the equilibrium is achieved through i) fee adjustments or ii) flow of money adjustments. Through fee adjustments, funds with higher fund fees should have higher expected risk-adjusted returns. Conversely, underperforming funds should have lower fund fees (Gil-Bazo et al., 2009). Through the flow of money adjustments, if returns decrease with fund size, funds with higher expected risk-adjusted returns should attract higher money flows to reduce the fund's expected performance to reach equilibrium. Thus, the risk-adjusted returns after expenses should be normalized for all funds (Berk and Green, 2004).

In this regard, equilibrium requires that expected risk-adjusted returns after expenses should be zero for all funds (Berk and Green, 2004). This requirement implies that a linear relationship exists between compensation fees and expected risk-adjusted returns before expenses, with a slope of one (Gil-Bazo et al., 2009).

7.1. Empirical methodology

To investigate the link between fund fees and performance for Colombian investment funds from 2009 to 2015, we regress the fund compensation fee and the expected risk-adjusted return before expenses, as calculated in Chapter 5, following the methodology employed by Gil-Bazo et al. (2009). The model specification is as follows:

$$\boldsymbol{\overline{Y}_{i,t}} = \boldsymbol{\alpha}_0 + \boldsymbol{\beta}\, \boldsymbol{TER_{i,t}} + \boldsymbol{\varepsilon_{i,t}} \qquad (18)$$

where $\boldsymbol{TER_{i,t}}$ is the total expense ratio for fund *i* and $\boldsymbol{\overline{Y}_{i,t}}$ is the risk-adjusted performance before expenses computed based on the models employed in Chapter 5. We estimate our regression using the pooled ordinary least squares (OLS) method. The residuals are clustered using the entire sample that employs the heteroskedasticity-robust standard error in White (1980). Further, to account for the cross-sectional correlation of residuals, we also cluster the residuals by month and fund following Petersen (2009) and Thompson (2006). The regression includes month dummies to ensure that the estimated slope coefficient captures the cross-sectional relationship between fees and risk-adjusted returns and not the effect of potentially correlated trends in those variables (Gil-Bazo et al., 2009: page 2159). We estimate the relationship between risk-adjusted performance before expenses ($\overline{\boldsymbol{Y}}_{\boldsymbol{i,t}}$) and fees (TER) using different performance models determined in Equations (14), (15), (16), and (17) to permit a power comparison and a robustness analysis.

7.2. Empirical results

Table 22 shows the estimated slope coefficients (see columns 4 and 8) for the OLS regression between monthly risk-adjusted performance before expenses for each fund and the main costs of delegated portfolio management that correspond to the TER (first group of columns) and the fee rate (advisory compensation fee) (second group of columns) from June 2009 to December 2015. TER is defined as the fee rate plus operating costs, such as administration, accounting, taxes, and agent fees. The fee rate is defined as the compensation rate paid by the investor to the advisory fund based on the fund's current total assets. We have estimated the relationship between fees and performance using the four models computed in Chapter 5. Table 22 shows i) the estimated slope coefficients using the customized benchmark Sharpe portfolio weights in the first group of rows; ii) the estimated slope coefficients using the approximated benchmark prospectus portfolio weights in the second group of rows; iii) the estimated slope coefficients in the third group of rows using the selection return (Sharpe, 1992; Christoffersen and Musto, 2002); and (iv) the estimated slope coefficients in the fourth group of rows using Carhart's four-factor model only for equity funds.

Table 22: Risk-adjusted performance before expenses measured according to different regression models defined in Chapter 5 and Expense Ratio.

			TER				Advisory´s compensation Fee (Fee rate)			
Risk-Adjusted Performance	Standard Errors		Coefficients	R2 adj.	Obs	p-value F	Coefficients	R2 adj.	Obs	p-value F
Sharpe Benchmark	White	Coef	0.172 **	0.61%	5996	0.000	0.380 **	0.64%	5996	0.000
		SE	0.088				0.150			
		t-value	1.960				2.524			
	Cluster by Time (Month)	Coef	0.172 **	0.61%	5996	0.000	0.380 *	0.64%	5996	0.010
		SE	0.087				0.198			
		t-value	1.972				1.914			
	Cluster by Time & Fund	Coef	0.172 **	0.61%	5996	0.000	0.380 **	0.64%	5996	0.000
		SE	0.082				0.162			
		t-value	2.098				2.344			
Prospectus Benchmark	White	Coef	0.118	1.79%	5996	0.000	0.227	1.79%	5996	0.000
		SE	0.100				0.178			
		t-value	1.180				1.278			
	Cluster by Time (Month)	Coef	0.118	1.79%	5996	0.000	0.227	1.79%	5996	0.016
		SE	0.157				0.271			
		t-value	0.754				0.838			
	Cluster by Time & Fund	Coef	0.118	1.79%	5996	0.000	0.227	1.79%	5996	0.000
		SE	0.097				0.190			
		t-value	1.222				1.198			
Selection Return - Sharpe	White	Coef	0.148 *	0.45%	8808	0.000	0.440 ***	0.55%	8808	0.000
		SE	0.084				0.128			
		t-value	1.765				3.443			
	Cluster by Time (Month)	Coef	0.148 *	0.45%	8808	0.000	0.440 **	0.55%	8808	0.026
		SE	0.084				0.219			
		t-value	1.764				2.013			
	Cluster by Time & Fund	Coef	0.148 *	0.45%	8808	0.000	0.440 ***	0.55%	8808	0.000
		SE	0.089				0.149			
		t-value	1.666				2.958			
Carhart (Equity Funds: Clust 1)	White	Coef	-0.871	18.90%	438	0.006	-1.040	18.71%	438	0.214
		SE	0.679				1.638			
		t-value	-1.284				-0.635			
	Cluster by Time (Month)	Coef	-0.871 **	18.90%	438	0.006	-1.040	18.71%	438	0.089
		SE	0.396				1.094			
		t-value	-2.199				-0.951			
	Cluster by Time & Fund	Coef	-0.871	18.90%	438	0.005	-1.040	18.71%	438	0.169
		SE	0.657				1.476			
		t-value	-1.326				-0.704			

This table shows estimated slope coefficients for the OLS regression of funds' monthly fee risk-adjusted performance before expenses on "total expense ratio" (TER) (first group of columns) – defined as the fee rate plus operating costs, such as, administration, accounting, taxes, agent fees; and on fee rate (Advisory´s compensation fee) (second group of columns) defined as the compensation rate paid by investor to the advisory fund on the basis of the current total asset of the fund, during the period from June 2009 to December 2015. Betas are estimated using the four models computed in Chapter 5: customized benchmark using Sharpe portfolio weights (first group of rows); approximated benchmark using prospectus portfolio weights (second group of rows); selection return (third group of rows); and Carhart´s four-factor model only for equity funds (fourth group of rows). Risk-adjusted performance in month *t* is estimated as the difference between the fund's monthly return before expenses in month *t* and the product of betas and the factor realizations for that month determined for each model. All regressions include dummies for months. Standard errors and t-statistics are reported below the estimated slope coefficients, respectively. Standard errors are clustered by White's (1980) heteroskedasticity-robust standard error by month and by time & fund, following Petersen (2009) and Thompson (2006). Adjusted R2 statistics are reported in percentage. $*$, $**$, $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The column p-value F is the statistical that denote if the null hypothesis of a unit coefficient is rejected whether at the 10%, 5%, or 1% significance levels. The number of observations is reported in column six and column ten.

The first row of each group of rows in Table 22 shows the beta-coefficient estimated using the entire sample of investment funds in Colombia clustered by the heteroskedasticity-robust standard error from White (1980). As is observed in the group of columns (TER), the estimated slope coefficient using the customized benchmark Sharpe portfolio weights is 0.17 and is statically significant at the 5% level. The estimated slope coefficient using the prospectus benchmark portfolio weights is 0.12 and is not significant. The estimated slope coefficient using the selection return is 0.15 and is statically significant at the 10% level. Finally, the estimated slope coefficient using Carhart's four-factor model only for equity funds is –0.87 and is not significant. Considering a unit slope for all regression models, we can reject the null hypothesis at any significance level.

Although the estimated coefficient using the prospectus benchmark portfolio weights is not statistically significant at any level, we might not state that, under this method, the fund's fees are not related to performance before expenses. Rather, we should interpret this result as follows: the prediction of the risk-adjusted performance using the approximation benchmark based on prospectuses is nosier than the risk-adjusted performance using our customized benchmark based on the Sharpe portfolio weight. This result is consistent with our hypothesis that investors in Colombia do not have enough and accurate information to evaluate investment fund performance.

The estimation of Equation (18) yields the results of a positive relationship between TER and the expected risk-adjusted returns before expenses. However, if we analyze only equity funds (fourth group of rows), the results of Equation (18) are consistent with previous research (Gil-Bazo et al., 2009)—a negative relationship between fund fee and performance.

If the theory predicts that investment fund fees should be positively correlated with the expected risk-adjusted returns before expenses in a frictionless competitive market and should have, in equilibrium, zero expected risk-adjusted returns after expenses (Berk and Green, 2004; Gil-Bazo et al., 2009), in a market with frictions, as posited by Gil-Bazo (2009: page 2159), whether we should expect a slope coefficient, $\boldsymbol{\beta}$, greater or less than one is not clear.

In this regard, our investigation generates interesting results. We observe that, on average, investment funds with higher performance charge higher fees ($\mathbf{0} < \boldsymbol{\beta} < \mathbf{1}$), but this performance is not enough to compensate for the differences in performance after expenses. For instance, the estimated slope coefficient in our first model (Sharpe benchmark, first group of rows in Table 22) shows that an increase of 1% in TER generates an increase of 0.17% in alpha. Thus, funds that charge higher fees have better performance before expenses but worse performance after expenses. Similar results arise when observing the estimated slope coefficient for the next two models. However, the estimated slope coefficient in the fourth model (Carhart's four-factor model, fourth group of rows in Table 22) shows a totally different result. The estimated beta is negative and different from zero at any significance level (beta coefficient cluster by month), suggesting that equity funds with worse performance before expenses charge higher fees ($\boldsymbol{\beta} < \mathbf{0}$).

The aforementioned results are also consistent if only the fee rate—advisory compensation fee (second group of columns in Table 22)—is analyzed. The estimation of Equation (18) yields the results of a positive relationship between the fee rate and the expected risk-adjusted returns before expenses for the first three models and a negative relationship between fund fees and performance for the fourth model (equity funds). Considering a unit slope for the three regression models, we can reject the null hypothesis at any significance level.

In this circumstance, the only plausible scenario in which funds obtain higher performance after expenses with higher fees is when the estimated slope coefficient is greater than 1 ($\boldsymbol{\beta} > \mathbf{1}$). This finding implies, as posited by Gil-Bazo (2009), that any increase in fees should be compensated by a higher increase in performance before expenses. However, under our results, we might not see this plausible scenario.

Following Gil-Bazo et al. (2009), we compute robust standard errors clustered by month (Petersen, 2009; Thompson, 2006) to account for the cross-sectional correlation of residuals. The second row for each group of the regression model in Table 22 shows that the robust standard error clustered by month is 0.09 using the customized benchmark Sharpe portfolio weights; 0.16 using the prospectus benchmark portfolio weights; 0.08 using the selection return; and 0.39 using Carhart's four-factor model only for equity funds. Other than the prospectus benchmark, these robust standard errors are not larger than the White standard error (0.09, 0.08, and 0.68, respectively). Thus, reasons exist to believe in the inexistence of any cross-sectional correlation in the residuals.

The robust standard error clustered by month using the prospectus benchmark portfolio weights (second group of rows) (0.16) is 60% larger than the White standard error (0.1). Thus, using this method, reasons exist to believe that the residuals have a cross-sectional correlation. This result is very interesting in our case because portfolio weights reported by prospectuses might be much more ambiguous and less precise. Thus, two investment funds that follow different strategies might appear to be similar, generating the presence of a cross-sectional correlation in the residuals. This result is also consistent with our hypothesis that investors in Colombia do not have accurate information to evaluate the performance of investment funds.

In addition, we cluster by both month and fund to also account for correlated residuals. These robust standard errors are reported in the third row of Table 22 for each group of the regression model. In the first group of columns (TER), the standard errors clustered by both month and fund (0.08, 0.10, 0.09, and 0.66, respectively) slightly change the White standard error (0.09, 0.10, 0.08, and 0.68, respectively). Therefore, in this section, we report robust standard errors clustered by time.

Following Gil-Bazo et al. (2009), we investigate the influence of small funds that survived during our sample period to analyze whether fund size has a relevant role in explaining the relationship between fund expenses and risk-adjusted performance. Then, we exclude from our sample the lowest amount of total assets of all investment funds in Colombia (the decile of monthly total assets observation). Thus, we re-estimate Equation (18) excluding these observations. Panel A of Table 23 shows the estimated slope coefficients excluding small funds for the OLS regression of funds' monthly fee and risk-adjusted performance before expenses and TER under the three different risk-adjusted performance models: i) customized benchmark using Sharpe portfolio weights, ii) approximate benchmark using prospectus portfolio weights, and iii) selection return. For each of the three different risk-adjusted performance models, the estimated slope coefficient is 0.22, 0.14, and 0.22, respectively, and these coefficients are statistically significant at the 10% and 5% levels only for the benchmark Sharpe and selection return, respectively. Considering a unit slope for the regression model, we also reject the null hypothesis. This result is consistent with our previous result. By eliminating small funds from our sample, we observe that the influence of fund size does not play a role in explaining the relationship between fund expenses and risk-adjusted performance. However, we observe that larger funds—by charging higher fees—have an average 30% better performance before expenses than small funds (0.22 coefficient in Table 23 compared with 0.17 coefficient in Table 22, Sharpe benchmark). However, this increase in performance is not enough to offset the difference in fees.

Table 23: Regressions by Subsamples, employing three different risk-adjusted performance models: i) customized benchmark using Sharpe portfolio weights, ii) approximated benchmark using prospectus portfolio weights, iii) selection return.

		Sharpe Benchmark			Prospectus Benchmark			Selection Return		
		TER			TER			TER		
Subsample		Coefficients	R2 adj.	Obs	Coefficients	R2 adj.	Obs	Coefficients	R2 adj.	Obs
Panel A: Effect of small funds										
Deciles 2-10	Coef	0.219 *	0.80%	5448	0.136	3.22%	5448	0.219 **	0.57%	7911
	SE	0.121			0.157			0.089		
	t-value	1.814			0.864			2.452		
Panel B: Effect of funds with front and back loads										
No front and back loads funds	Coef	0.202 **	0.73%	5951	0.138	1.81%	5951	0.186 **	0.51%	8717
	SE	0.086			0.162			0.090		
	t-value	2.344			0.851			2.068		
With front and back loads funds	Coef	0.163	-0.07%	1960	0.043	1.21%	1960	0.052	-0.12%	2920
	SE	0.149			0.243			0.129		
	t-value	1.090			0.178			0.402		
Panel C: Effect of funds with performance Fee Incentives										
No Performance Fee Incentive	Coef	0.138	0.57%	5951	0.117	1.41%	5951	0.118	0.41%	7621
	SE	0.115			0.168			0.107		
	t-value	1.204			0.698			1.107		
With Performance Fee Incentive	Coef	0.250 ***	2.95%	831	0.092	7.96%	831	0.235 ***	1.19%	1187
	SE	0.064			0.176			0.055		
	t-value	3.882			0.523			4.259		
Panel D: Regressions by Investment Objective under cluster GSC										
Cluser 1: Equity - growth	Coef	0.230	3.03%	438	0.212	3.09%	438	-0.137	3.41%	708
	SE	0.354			0.375			0.396		
	t-value	0.649			0.564			-0.345		
Cluster 2: Money market	Coef	0.370 ***	3.12%	4497	0.318 **	10.20%	4497	0.415 ***	3.41%	6489
	SE	0.050			0.134			0.049		
	t-value	7.343			2.369			8.511		
Cluster 3: Debt	Coef	0.219 **	2.99%	750	0.106	2.08%	750	0.295 **	2.77%	1108
	SE	0.111			0.141			0.130		
	t-value	1.970			0.749			2.260		
Cluster 4: Balanced	Coef	-1.115 **	1.31%	181	-0.812	15.88%	181	-0.521	-1.56%	304
	SE	0.462			0.745			0.861		
	t-value	-2.413			-1.090			-0.605		
Cluster 5: Income	Coef	-6.950 **	10.16%	130	-8.519 **	13.77%	130	-4.106	2.77%	199
	SE	2.948			3.356			3.688		
	t-value	-2.357			-2.539			-1.113		
Time Dummy		Yes			Yes			Yes		
Clustering		Month level			Month level			Month level		

This table shows estimated slope coefficients for the OLS regression of funds' monthly fee risk-adjusted performance before expenses on "total expense ratio" (TER), during the period from June 2009 to December 2015 for panels A, B, C and D. Betas are estimated using the three models computed in Chapter 5: i) customized benchmark using Sharpe portfolio weights (first group of columns); ii) approximated benchmark using prospectus portfolio weights (second group of columns); iii) selection return (third group of columns). Risk-adjusted performance in month *t* is estimated as the difference between the fund's monthly return before expenses in month *t* and the product of betas for that month determined for each model. Monthly fees correspond to TER defined as the fee rate plus operating costs, such as, administration, accounting, taxes, agent fees. This monthly fee is used in all panels. In Panel A the sample does not include for each month the decile of fund-month observations with the lowest total assets among all investment funds. In Panel B we have classified the sample in those with No front-end and back-end loads and those with front-end and back-end loads. In Panel C we have classified the sample in those with No performance incentives and With Performance incentives. In Panel D we have estimated the slope coefficients for the OLS regression of funds' monthly fee risk-adjusted performance before expenses on TER, under our five empirical style categories (GSC). All regressions include dummies for months. Standard errors and t-statistics are reported below the estimated slope coefficients, respectively. Standard errors are clustered by time (month). Adjusted R2 statistics are reported in percentage. ∗, ∗∗, ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The number of observations is reported in column five, eight and eleven.

In our analysis, we have considered the TER and the fee rate (advisory's compensation fee) as the main costs of the delegated portfolio management. However, as described in Chapter 3, investors in Colombia often pay for some funds' front-load (at the time of purchasing any asset) or back-load (at the time of redeeming any asset) fees, as well as contractual incentives based on performance-based fees. In this regard, our regressions capture, on average, a positive relationship between performance and fund fees. Considering that load funds and performance incentive funds might be the most expensive funds and constitute a small part of our sample, we estimate the relationship between performance and fund fee if we exclude those funds from our sample (funds with front-end and back-end loads, and performance incentives funds), following the methodology in Gil-Bazo et at. (2009).

Thus, we re-estimated Equation (18), excluding load and performance incentive funds. Panels B and C of Table 23 show the estimated slope coefficients excluding load and performance incentive funds for the OLS regression of funds' monthly fee risk-adjusted performance before expenses and TER for the three different risk-adjusted performance models. As Panel B indicates for each of the three different risk-adjusted performance models, the estimated slope coefficients for "no front-end and back-end loads" are 0.20, 0.14, and 0.19, respectively, and are statically significant at 5% level for the first (Sharpe benchmark) and third (section return) models. This result is interesting because, by excluding the most expensed funds (funds with load expenses), we still observe a positive relationship between TER and risk-adjusted performance before expenses for load and no-load funds, but load funds follow a different strategy. The estimated coefficient for no-load funds is higher than load funds, suggesting that the most expensive funds through higher fees have worse performance before expenses.

Panel C of Table 23 shows that the estimated slope coefficients for funds with performance fee incentives for each of the three different risk-adjusted performance models are 0.25, 0.09, and 0.23, respectively, and they are statically significant at the 1% level for the first (Sharpe benchmark) and third (section return) models. This result is also interesting because the relationship is still positive. However, funds for which the fee is tied to the fund's performance has almost twice the performance before expenses than funds with no performance incentive.

As a final test of the robustness analysis, we re-estimate Equation (18) into subsamples according to our empirical style categories (GSC) determined in section 4.3.4. Panel D of Table 23 shows the estimated slope coefficients under our five empirical style categories for the OLS regression of TER and the monthly risk-adjusted performance before expenses for each fund, employing the three different risk-adjusted performance models detailed in Chapter 5. Panel D of Table 23, which provides the regression results between risk-adjusted performance on the Sharpe benchmark and TER (first group of columns), shows that the estimated slope coefficient has a mixed effect by investment objective. Clusters 1, 2, and 3 have estimated coefficients of 0.23, 0.37, and 0.22, respectively, suggesting a positive relationship between a fund's performance and fees. However, the excess fees are not high enough to fully compensate for the differences in performance before expenses. We can reject the null hypothesis for clusters 2 and 3 at the 1% and 5% significance levels, respectively, considering the unit slope for the regression model. Clusters 4 and 5 have statically significant estimated coefficients of –1.16 and –6.95, respectively, suggesting a negative relationship between a fund's performance and fees.

These regression results are very interesting. For instance, the estimated coefficient in cluster 2 (0.37) is more than twice the average estimated coefficient for all funds (0.17 coefficient in Table 22, Sharpe benchmark), suggesting that money market funds (representing more than two-thirds of the sample)—by charging higher fees—have on average more than twice the performance before expenses than the other funds. However, this excess is still not enough to offset the performance after expenses, a result that is statistically significant at the 1% level. The same conclusion might be taken for the equity and debt funds (clusters 1 and 3) but at a lower proportion. However, for clusters 4 and 5—for which the strategic investment for cluster 4 follows a balanced portfolio with the highest weights in Government bills and liquid stocks (see section 4.3.4) and for cluster 5 pursues the highest weights in the COLCAP index and then a representative proportion in cash balances (see section 4.3.4)—the relationship is negative, suggesting that these funds with worse performance before expenses charge higher fees than other funds.

The estimated coefficients in Panel D for the other two regression models (second and third group of columns Table 23) show similar results except for cluster 1 (equity funds) in the selection return method (three groups of columns).

The funds classified under this cluster have a negative relationship, which is consistent with the results obtained in clusters 4 and 5 and with previous research for equity funds (Gil-Bazo et al., 2009). In addition, the conclusion we obtain under the prospectus benchmark (second group of columns) is similar to our prior results but are noisier than the results obtained under the customized benchmark of the Sharpe portfolio model (first group of columns), suggesting than the portfolio weights reported by the prospectus might be much more ambiguous and less precise.

7.3. Interpretation

To summarize our results under this univariate regression, we find that investment funds in Colombia have, on average, a positive relationship between risk-adjustment performance and fees; that is, funds that charge higher fees have better performance before expenses but worse performance after expenses. These results agree with the intuitive expectation that the value created for investors is a reflection of the fees charged. However, we find mixed results when we see this relationship by investment objectives based on our empirical style classification. Funds classified as money market and debt (clusters 2 and 3) have a positive relationship, whereas funds classified as equity, balanced, or income (clusters 1, 4, and 5) have a negative relationship. This negative relationship also has been consistent with prior research, for example, Gil-Bazo et al. (2009) and Christoffersen and Musto (2002), because these authors showed a negative relationship between performance and fees for equity and money market funds, respectively.

One potential explanation for our results, as posited by Gil-Bazo et al. (2009), is that fund performance might be positively related to its total expenses because higher expenses might be synonymous with larger investments in research tools and higher salaries for "more talented managers," as is the case for funds classified in clusters 2 and 3. In addition, investment funds with better performance intend to keep fees low—reflecting a negative relationship—because this condition incentivizes the competition to attract "performance-sensitive investors" (Gil-Bazo et al., 2009).

However, some arguments for a negative relationship between a fund's fees and performance are as follows. As Gil-Bazo et al. (2009) posited, one of the main explanation of this negative relationship is lowering the fund's operating costs. If fees reflect the costs of operating a fund, then having low costs should be associated with better performance and, hence, a negative relationship between performance and fees might result. As they stated, a fund's operating costs can be reduced in different ways. For larger funds, economies of scale might explain the reduction in operating costs. Better performance might be associated with a larger size if that performance is persistent with past results, suggesting a lower operating cost. Learning economies might also reduce the operating costs for older funds if they are able to translate their experience in the form of lower funds onto investors. Having better managers might also be associated with lower operating costs because talented managers may make better investment decisions and make the fund's operation more efficient. Another explanation for this negative relationship, as posited by Christoffersen and Musto (2002) for money market funds, is that funds with persistent worse performance will not be attractive for current investors (less performance-sensitive); thus, they will abandon those funds following a bad performance. Therefore, these underperforming funds charge higher fees because they realize that doing so is not associated with a larger flow of money out of the fund (Christoffersen and Musto, 2002; Gil-Bazo et al., 2009). In this regard, Gil-Bazo (2009) also stated that funds with bad performance traditionally charge higher fees because they realize that they cannot compete with better performing funds and, thus, focus on investors that are not sensitive to performance.

Although our results show, on average, a positive relationship between a fund's fees and performance, we find evidence that might coincide with prior research that showed that having low operating costs are associated with better performance. Table 22 shows that the difference in the estimated coefficient between the regression models using TER (first group of columns) and fee rate (second group of columns) result in better performance through a lower fee rate (fee rate does not include any costs associated with accounting, taxes, and others). These estimated coefficients between risk-adjusted performance and fee rate (advisory compensation fee) are higher in most cases (0.38, 0.23, 0.44, –1.04) relative to the estimated coefficient between risk-adjusted performance and TER (0.17, 0.12, 0.15, –.87), suggesting a reasonable presence of better fund performance when the fund's cost is lower.

Given that these results are the product of the univariate regression, in the next section, we explain this relationship between fees and performance.

8. DETERMINANTS OF FUND FEES

In this section, we explain the relationship between fees and performance analyzed in Chapter 6 to investigate how fund characteristics might have affected a fund's compensation fee from 2009 to 2015.

8.1. Empirical Methodology

8.1.1. Fund flow determinants and flow-to-performance sensitivity

To explain the link between a fund's compensation fees and the underlying portfolio characteristics, we should regress the fund's fee rate with a set of funds variables, flow-to-performance sensitivity, and performance. However, before engaging in this analysis, we first investigate the determinants of fund flows and compute the flow-to-performance sensitive.

To determine the flow-to-performance sensitivity, $\boldsymbol{Sensitivity}\ (\boldsymbol{S})_{i,t}$, we follow the methodology employed by Gil-Bazo et al. (2009). The sensitivity of flows to past performance is a function of performance and fund characteristics (Gil-Bazo et al., 2009). The flow-to-performance sensitivity, $\boldsymbol{Sensitivity}\ (\boldsymbol{S})_{i,t}$, is determined in two steps. First, we investigate the determinants of fund flows. Second, using the estimated determinants of fund flows (first step), we estimate flow-to-performance sensitivity, $\boldsymbol{Sensitivity}\ (\boldsymbol{S})_{i,t}$, for each fund and month as the first derivative of the conditional expected flow for performance (Gil-Bazo et al., 2009: page 2181).

As a first step to investigating the determinants of fund flows, we follow the methodology used by Gil-Bazo et al. (2009), which is also built on the literature of mutual fee determinants considered from prior studies on fund flows; see, for example, Sensoy (2009); Gil-Bazo et al. (2009); Huang, Wei, and Yan (2007);

Barber, Odean, and Zheng (2005); Nanda, Wang, and Zheng (2005); Christoffersen and Musto (2002); Jain and Wu (2001); Sirri and Tufano (1998); Chevalier and Ellison (1997); Gruber (1996); Ippolito (1992).

These studies indicated that flows of money, $\boldsymbol{Fund\ Flow_{i,t}}$, are positively related to performance after expenses. In addition, the flow-to-performance sensitivity is higher for funds with a strong performance (implying a convex curve of flow-to-performance) and lower for funds with weak performance. Further, the flow-to-performance sensitivity becomes reducing (less convex) when the fund's compensation fee decreases (Gil-Bazo et al., 2009; Huang, Wei, and Yan, 2007). As posited by Christoffersen and Musto (2002), funds with the least performance-sensitive investors experienced high money outflows; that is, a positive relationship exists between flow-to-performance and performance sensitivity. Finally, these prior studies also showed that flows of money, $\boldsymbol{Fund\ Flow_{i,t}}$, depend on fund size, age, TER, total money flows into funds, lagged flows, volatility, lagged expected performance return, and performance sensitivity.

To measure performance sensitivity, $\boldsymbol{Q/MAX_{i,t}}$, we include the following proxy for performance sensitivity employed by Gil-Bazo et al. (2009: page 2180) and proposed by Christoffersen and Musto (2002):

$$\boldsymbol{Q/MAX_{i,t}} = \frac{\boldsymbol{FundTA_{i,t}}}{\boldsymbol{MAX\ (FundTA_{i,t})}}$$

These authors used total net asset value in month *t* (*TNA*) of fund *i* to compute performance sensitivity. However, in our case, given that we have the total asset value of funds before expenses, $\boldsymbol{FundTA_{i,t}}$, at the beginning of period *t*, we replace *TNA* for $\boldsymbol{FundTA_{i,t}}$, which we believe is the best approximation for computing performance sensitivity. $\boldsymbol{MAX}$ ($\boldsymbol{FundTA_{i,t}}$) is the maximum total asset fund *i* during the entire sample.

The model specification to investigate the determinants of fund flows, following the methodology used by Gil-Bazo et al. (2009) and Sensoy (2009), is as follows:

$$\boldsymbol{Fund\ Flow_{i,t}} = \boldsymbol{\alpha}_{0,t} + \boldsymbol{\beta_0}\boldsymbol{\overline{Y}_{i,t-1}} + \boldsymbol{\beta_1}\boldsymbol{\overline{Y}_{i,t-1}} * \boldsymbol{Age_{i,t-1}} + \boldsymbol{\beta_2}\boldsymbol{\overline{Y}_{i,t-1}} * \boldsymbol{Q/MAX_{i,t-1}} + \boldsymbol{\delta Fund\ Char_{i,t-1}} + \boldsymbol{\lambda TER_{i,t-1}} + \boldsymbol{\eta Q/MAX_{i,t-1}} + \boldsymbol{\varepsilon_{i,t}} \quad (19)$$

where $\boldsymbol{Fund\ Flow_{i,t}}$ (or *new money inflow*) is the measure computed in section 3.3.2, which is defined as the percentage growth in total assets under management (in local currency) between the beginning and the end of month *t*, net of internal growth (assuming reinvestment of returns or dividends) (Ferreira et al., 2012). $\boldsymbol{\overline{Y}_{i,t}}$ is the expected risk-adjusted performance before expenses measured according to the models employed in Chapter 5. The variables $\boldsymbol{Age_{i,t..}}$ and $\boldsymbol{Q/MAX_{i,t..}}$ are the natural log of the age of the fund and the natural log of the Q/MAX variable, respectively. $\boldsymbol{TER_{i,t-1}}$ is the fund's total expense ratio for fund *i* (Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Sensoy, 2009). The vector $\boldsymbol{FundChar_{i,t-1}}$ considers the following lagged variables that might influence the determinants of fund flows: fund size, which is the natural log of a fund's total asset value; family fund size, which is the natural log of total asset value grouped by fund family; and fund age, which is the natural log of the number of years since the fund's organization; Volatility is the standard deviation of the monthly return of each fund during the last twelve months; fund flow is the new money inflow computed as the net inflow into the fund as a percentage of total assets; and dummy variables identify the front loads, back loads, and performance incentives. In addition, $\boldsymbol{\varepsilon_{i,t}}$ is the generic error term. We include a dummy variable to identify the five funds' investment objectives calculated under our empirical style categories computed in section 4.2.4. We also include month dummies in all regressions. The regression is estimated using the pooled OLS method. We cluster the residuals by the heteroskedasticity-robust standard from White (1980), and the t-statistics are also clustered by month and at the fund level to account for autocorrelation in fund compensation fees.

As a second or last step, we estimate the flow-to-performance sensitivity, $\boldsymbol{Sensitivity\ (S)_{i,t}}$, as the first derivative of the conditional expected flow for performance, given the estimated coefficients in Equation (20) (Gil-Bazo et al., 2009: page 2181). The model specification is as follows:

$$\boldsymbol{Sensitivity\ (S)_{i,t}} = \frac{d\, E_{t-1}(\boldsymbol{Fund\ Flow_{i,t}})}{d\, \boldsymbol{\overline{Y}_{i,t-1}}} \qquad (20)$$

where $\boldsymbol{E_{t-1}}$ denotes, as posited by Gil-Bazo (2009), the expectation operator conditional at time *t – 1.* However, this equation can be rewritten as follows:

$$\boldsymbol{Sensitivity\ (S)_{i,t}} = \boldsymbol{\widehat{\beta}}_0 + \boldsymbol{\widehat{\beta}_1} * \boldsymbol{Age_{i,t-1}} + \boldsymbol{\widehat{\beta}_2} * \boldsymbol{Q/MAX_{i,t-1}} \qquad (21)$$

where $\boldsymbol{\widehat{\beta}_n}$ is the estimated coefficient $\boldsymbol{\beta_n}$ in Equation (20); and $\boldsymbol{Age_{i,t-1}}$ and $\boldsymbol{Q/MAX_{i,t-1}}$ are the natural log of the age of the fund and the natural log of Q/MAX, respectively.

Finally, the variable $\boldsymbol{Sensitivity\ (S)_{i,t}}$ is then used in Equation (22) to explain the link between a fund's compensation fees and the underlying portfolio characteristics.

8.1.2. *Relationship between fund compensation fees and fund characteristics*

Once we have computed the flow-to-performance sensitivity, $\boldsymbol{Sensitivity}\ (\boldsymbol{S})_{i,t}$, we proceed to explain in this section the link between a fund's compensation fees and its underlying portfolio characteristics by regressing its fee rate with a set of fund variables described in Chapter 3, flow-to-performance sensitivity, $\boldsymbol{Sensitivity}\ (\boldsymbol{S})_{i,t}$, and performance, following the methodology employed by Gil-Bazo et al. (2009). The model specification is as follows:

$$\boldsymbol{TER}_{i,t} = \beta_{\mathbf{0}} + \boldsymbol{\gamma}^{'}\boldsymbol{FundChar}_{i,t-1} + \boldsymbol{\theta}\boldsymbol{Sensitivity}\ (\boldsymbol{S})_{i,t} + \boldsymbol{\lambda}\overline{\boldsymbol{Y}}_{i,t} + \boldsymbol{\varepsilon}_{i,t} \quad (22)$$

where $\boldsymbol{TER}_{i,t}$ is the fund's total expense ratio for fund *i*, $\boldsymbol{FundChar}_{i,t-1}$ is a vector of lagged underlying portfolio fund characteristics that are likely to determine the fund's compensation fees, $\boldsymbol{Sensitivity}\ (\boldsymbol{S})_{i,t}$ is the performance sensitivity of the fund's flows (Gil Bazo et al., 2009), $\overline{\boldsymbol{Y}}_{i,t}$ is the expected risk-adjusted performance before expenses measured according to the models employed in Chapter 5, and $\boldsymbol{\varepsilon}_{i,t}$ is the generic error term.

We build the aforementioned relationship on the finance literature, which was studied by different authors, such as Gil-Bazo et al. (2009); Golec (2003); Deli (2002); Luo (2002); Chalmers, Edelen, and Kadlec (2001); Malhotra and McLeod (1997); Latzko (1999); and Tufano and Sevick (1997). These authors considered fund fees as a linear function of lagged variables that are likely to determine the fund's compensation fee. Thus, the vector $\boldsymbol{FundChar}_{i,t-1}$ considers the following lagged measures that may impact the costs of operating a fund: fund size, which is the natural log of a fund's total asset value; family fund size, which is the natural log of the total asset value grouped by the family of funds; fund age, which is the natural log of the number of years since the fund's organization; turnover, which is the estimated variable for the lesser of fund purchases or sales divided by the total asset value; volatility, which is computed as the standard deviation of the fund's monthly returns during the last twelve months; and fund flow, which is the new money inflows computed as net inflows into the fund as a percentage of total assets. We include a dummy variable to identify the five funds investment objectives calculated under our empirical style categories computed in section 4.2.4. We also include month dummies in all regressions to account for cross-sectional dependence. The regression is estimated using the pooled OLS method. We cluster residuals using the heteroskedasticity-robust standard error from White (1980), and the t-statistics are clustered by month and at the fund level to account for the autocorrelation in fund compensation fees.

8.2. Empirical results

8.2.1. Results of flow determinants and performance sensitivity

Table 24 shows the results of the determinants of the flows to funds for the OLS regression estimated in Equation (19). We have estimated these determinants using the three models computed in chapter 5. Table 22 shows the following: i) in the third column, the determinants of flows to funds using the customized benchmark Sharpe portfolio weights (column called Risk-Adjusted Benchmark Sharpe); ii) in the fourth column, the determinants of flows to funds using the approximated benchmark prospectus portfolio weights (column called Risk-Adjusted Benchmark Prospectus); and iii) in the fifth column, the determinants of flows to funds using the selection return (column called Selection Return

- Sharpe). Robust standard errors clustered by time are reported in all linear regressions because the standard errors clustered by White and by time*x*fund slightly change the White standard error.

Table 24 shows that flows are not affected by the past (relative) performance of investment funds in Colombia or that the effect is small. The coefficient in the three regression models used is negative, very small, and not statistically significant. In other words, any variation in a fund's past performance reduces the money inflows in a much more modest way; that is, investors are not sensitive to past performance. In our case, this finding is very interesting because it suggests that negative performance relative to the benchmark reduces flows, and relatively sophisticated investors in Colombia appear to penalize funds for poor performance (Sensoy, 2009). Our result is inconsistent with previous studies in which flows are positively related to historical returns and have substantial explanatory power for fund flows (Sensoy; 2009; Gil-Bazo et al., 2009; Huang, Wei, and Yan, 2007; Barber, Odean, and Zheng, 2005; Nanda, Wang, and Zheng, 2005; Jain and Wu, 2001; Sirri and Tufano, 1998; Chevalier and Ellison, 1997; Gruber, 1996; Ippolito, 1992).

Table 24: Determinants of flows to funds and performance sensitivity, under three different risk-adjusted performance models: i) customized benchmark Sharpe portfolio weights, ii) approximated benchmark prospectus portfolio weights, iii) selection return.

Variable		Risk-Adjusted Benchmark Sharpe	Risk-Adjusted Benchmark Prospectus	Selection Return - Sharpe
Alpha: Risk-Adjusted Return (t-1)	Coef	-0.005	-0.009	-0.001
	SE	0.047	0.022	0.019
	t-value	-0.098	-0.405	-0.069
Perf*Ln Age (t-1)	Coef	0.001	0.000	-0.001
	SE	0.009	0.005	0.004
	t-value	0.107	-0.085	-0.246
Perf*Q/MAX (t-1)	Coef	0.000	-0.005	-0.007
	SE	0.008	0.005	0.007
	t-value	-0.053	-0.999	-0.969
Ln, Family Total Asset (t-1)	Coef	0.005	0.005	0.010
	SE	0.007	0.007	0.008
	t-value	0.741	0.731	1.289
Ln, Fund Total Asset (t-1)	Coef	0.004	0.004	0.006
	SE	0.006	0.006	0.004
	t-value	0.705	0.729	1.271
Ln, Fund Age (t-1)	Coef	-0.021 ***	-0.021 ***	-0.029 ***
	SE	0.008	0.008	0.008
	t-value	-2.682	-2.721	-3.661
TER (t-1)	Coef	-0.101 ***	-0.100 ***	-0.115 ***
	SE	0.033	0.032	0.026
	t-value	-3.102	-3.085	-4.446
Fund Volatility (t-1)	Coef	0.004	0.004	0.009
	SE	0.019	0.019	0.014
	t-value	0.194	0.206	0.642
Fund Flow (t-1)	Coef	-0.030 *	-0.031 *	-0.039
	SE	0.016	0.016	0.026
	t-value	-1.939	-1.940	-1.522
Q/MAX (t-1)	Coef	0.020 *	0.019	-0.009
	SE	0.012	0.012	0.026
	t-value	1.668	1.589	-0.358
Front_load Dummy	Coef	-0.087 ***	-0.082 ***	-0.084 ***
	SE	0.018	0.017	0.014
	t-value	-4.838	-4.924	-5.907
Back_load Dummy	Coef	0.026	0.027	0.028 *
	SE	0.016	0.017	0.017
	t-value	1.593	1.632	1.665
Performance Incentive Dummy	Coef	-0.009	-0.009	-0.008
	SE	0.009	0.010	0.008
	t-value	-0.915	-0.906	-1.066
Intercept	Coef	0.044	0.040	-0.078
	SE	0.096	0.094	0.127
	t-value	0.456	0.424	-0.613
Time Dummy		Yes	Yes	Yes
Investment Objective Dummy		Yes	Yes	Yes
Clustering		Month level	Month level	Month level
Observation		5894	5894	7321
R2 adj		0.67%	0.70%	0.36%

This table shows the regression of the determinants of flows to funds of the form: $\boldsymbol{Fund\ Flow_{i,t}} = \boldsymbol{\alpha_{0,t}} + \boldsymbol{\beta_0 \overline{Y}_{i,t-1}} + \boldsymbol{\beta_1 \overline{Y}_{i,t-1}} * \boldsymbol{Age_{i,t-1}} + \boldsymbol{\beta_2 \overline{Y}_{i,t-1}} * \boldsymbol{Q/MAX_{i,t-1}} + \boldsymbol{\delta Fund\ Char_{i,t-1}} + \boldsymbol{\lambda TER_{i,t-1}} + \boldsymbol{\eta Q/MAX_{i,t-1}} + \boldsymbol{\varepsilon_{i,t}}$, where $\boldsymbol{Fund\ Flow_{i,t}}$ (or new money inflow) is the measure computed in section 3.3.2 of this document, which is defined as the percentage growth in total assets under management (in local currency) between the beginning and the end of a month *t*, net of internal growth (assuming reinvestment of returns or dividends). $\overline{\boldsymbol{Y}}_{i,t}$ is the expected risk-adjusted performance *(Perf)* before expenses measured according to the main three models employed in Chapter 5. The variables $\boldsymbol{Age}_{i,t..}$ and $\boldsymbol{Q/MAX}_{i,t..}$ are the natural log of the fund´s age and the natural log of fund´s Q/MAX, respectively. $\boldsymbol{TER}_{i,t-1}$ is the fund's total expense ratio for fund *i*. The vector $\boldsymbol{FundChar}_{i,t-1}$ consider the following lagged variables that might influence the fund flow determinants: Fund Size which is the natural log of fund total asset value; Family Fund Size which is the natural log of total asset value grouped by family of funds; Fund age which is the natural log of the number of years since the fund´s organization; Volatility computed as the standard deviation of the fund´s monthly return during the last twelve months; Fund Flow which is the new money inflow computed as net inflow into the fund as a percentage of total assets; dummy variables to identify the front loads, back loads and performance incentives. And $\boldsymbol{\varepsilon}_{i,t}$ is the generic error term. We include a dummy variable to identify the five funds' investment objective calculated under our empirical style categories computed in section 4.2.4 of this document. We also include month dummies in all regressions. The regression is estimated by pooled ordinary least squares (OLS). Standard errors and t-statistics are reported below the estimated slope coefficients, respectively. Standard errors are clustered by time (month). Adjusted R2 statistics are reported in percentage. $*$, $**$, $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The number of observations is reported in column three, four and five.

In addition, Table 24 shows that flows are negative relative to age. The coefficient of the variable (*Ln, Fund Age t–1)* is –0.021 and is significant at the 1% level for the three risk-adjusted performance models. This result is consistent with previous research (Sensoy; 2009; Gil-Bazo et al., 2009; Sirri and Tufano, 1998). Flows and performance sensitivity are positively associated with Q/Max. The result of Q/Max is significant at the 10% level for the benchmark Sharpe risk-adjusted performance models, which is consistent with the results obtained by Gil-Bazo et al. (2009) and Christoffersen and Musto (2002). Therefore, as shown by Christoffersen and Musto (2002), investment funds with the least performance-sensitive investors have experienced high money outflows, that is, a positive relationship between flow-to-performance and performance sensitivity. For the rest of the two regression models, the Q/Max result is not significant at any level.

The determinants of flows to funds shown in Table 24 reflect investors' strong reaction to changes in fees, which also appears to occur with relatively sophisticated investors in Colombia. Table 24 shows that flows are inversely related to changes in TER, and this negative relationship is significant at the 1% level for the three risk-adjusted performed models—results that are also consistent with previous research (Gil-Bazo et al., 2009; Sirri and Tufano, 1998; Chevalier and Ellison, 1997). These results imply that if funds increase their monthly fees (TER) by one standard deviation (standard deviation of TER is 0.123 percent from the mean), flows would decline by 1.24 basis points in a month (for the Risk-Adjusted Benchmark Sharpe model in column 3). The same conclusion is reached when front-load fees are considered. Flows are inversely related to front-load fees, a result that is significant at the 1% level for the three risk-adjusted performed models.

8.2.2. Results of determinants of fund fees and flow-to-performance sensitivity

Table 25 shows the results of the determinants of fund fees for the OLS regression estimated in Equation (22). We have estimated the fund's determinant compensation fees using the three risk-adjusted performance models computed in chapter 5. Table 25 shows i) in the first group of columns the fund's fee determinants using the customized benchmark Sharpe portfolio weights (column called Benchmark Sharpe); ii) in the second group of columns the fund's fee determinants using the approximated benchmark Prospectus portfolio weights (column called Benchmark Prospectus); and iii) in the third group of columns the fund's fee determinants using selection return (column called Selection Return). We use as the dependent variable $\boldsymbol{TER_{i,t}}$ (columns 1 and 2), which is the fund's total expense ratio for fund *i*. However, as the robustness analysis, we replace the independent variable TER by the Fee Rate (Advisory's compensation fee) (column 3), defined as the compensation rate paid by investor to the advisory fund on the basis of the current total asset of the fund (this fee rate does not include the operating cost of the funds). Column 2 in Table 25 presents the results of estimating Equation (22) without considering the sensitive of flow-to-performance measure in Equation (21). We show the results of robust standard errors clustered by time in all linear regressions because the standard errors clustered by White and by time and fund slightly change the White standard error.

As column 1 in Table 25 shows for all risk-adjusted performance models, the expected performance coefficient is positive and significantly different from zero. Thus, the positive relationship between performance and fees obtained in chapter 6 was not the consequence of omitting variables such as, size, age, and turnover, among others, that are likely, as posited by Gil-Bazo et al. (2009), to determine operating costs related to performance. An interesting result of our regression model is that, although the coefficient for expected performance remains positive, the impact of this coefficient on TER and fee rate is very modest. If we consider the coefficient in the benchmark Sharpe regression model, the result implies that, if funds increase monthly performance before fees by one standard deviation (standard deviation of performance of 0.718 percent from the mean), TER would increase by 0.57 basis points in a month. Therefore, this finding still confirms that funds with better performance charge higher fees, and this increase in performance is translated into investors. Conversely, funds with worse performance before fees charge even higher fees.

Table 25: Determinants of fund´s fee and flow-to-performance sensitivity measured according to different regression models defined in Chapter 5 and Expense Ratio.

		Benchmark Sharpe			Benchmark Prospectus			Selection Return		
		TER		Fee rate	TER		Fee rate	TER		Fee rate
Variable		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Alpha: Risk-Adjusted Return	Coef	0.008 ***	0.009 ***	0.004 **	0.006 ***	0.006 ***	0.002 *	0.006 ***	0.007 ***	0.003 **
	SE	0.002	0.002	0.002	0.002	0.002	0.001	0.001	0.001	0.001
	t-value	3.351	3.721	2.347	2.595	2.924	1.719	4.305	5.183	2.506
Ln, Fund Total Asset (t-1)	Coef	-0.020 ***	-0.015 ***	-0.008 ***	-0.020 ***	-0.015 ***	-0.008 ***	-0.018 ***	-0.013 ***	-0.008 ***
	SE	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000
	t-value	-27.391	-30.578	-32.176	-27.449	-30.915	-33.367	-26.175	-27.305	-52.067
Ln, Family Total Asset (t-1)	Coef	-0.010 ***	-0.011 ***	-0.007 ***	-0.010 ***	-0.012 ***	-0.007 ***	-0.011 ***	-0.012 ***	-0.008 ***
	SE	0.001	0.001	0.000	0.001	0.001	0.000	0.000	0.000	0.000
	t-value	-16.148	-19.639	-21.210	-15.750	-18.770	-20.723	-26.166	-34.171	-34.243
Ln, Fund Age (t-1)	Coef	0.057 ***	0.006 ***	0.032 ***	0.008 ***	0.006 ***	0.000	0.005 ***	0.004 ***	0.000
	SE	0.003	0.001	0.001	0.001	0.001	0.000	0.001	0.001	0.000
	t-value	17.413	7.146	25.028	8.381	7.451	0.446	7.051	6.144	-0.757
Turnover (t-1)	Coef	-0.004 ***	-0.009 ***	-0.015 ***	-0.004 ***	-0.009 ***	-0.015 ***	-0.006 ***	-0.010 ***	-0.012 ***
	SE	0.001	0.002	0.003	0.001	0.002	0.003	0.001	0.001	0.001
	t-value	-2.772	-4.618	-4.953	-2.819	-4.626	-4.929	-6.338	-8.289	-8.194
Fund Volatility (t-1)	Coef	-0.001	-0.001	-0.005 ***	-0.001	-0.001	-0.005 ***	-0.003 *	-0.003 **	-0.006 ***
	SE	0.002	0.002	0.001	0.002	0.002	0.001	0.002	0.002	0.001
	t-value	-0.629	-0.547	-4.986	-0.683	-0.613	-5.039	-1.773	-2.148	-7.034
Fund Flow (t-1)	Coef	-0.008 ***	-0.007 **	-0.006 ***	-0.008 ***	-0.006 **	-0.006 ***	-0.005 ***	-0.004 ***	-0.003 **
	SE	0.003	0.003	0.002	0.003	0.003	0.002	0.002	0.002	0.001
	t-value	-2.789	-2.383	-2.619	-2.776	-2.345	-2.590	-2.824	-2.626	-2.399
S_Flow to Performance	Coef	-50.670 ***		-32.847 ***	-4.135 ***		-2.677 ***	-3.175 ***		-1.906 ***
	SE	2.959		1.435	0.232		0.110	0.114		0.049
	t-value	-17.126		-22.891	-17.861		-24.402	-27.928		-38.641
Intercept	Coef	0.357 ***	0.563 ***	0.247 ***	0.558 ***	0.568 ***	0.377 ***	0.581 ***	0.561 ***	0.418 ***
	SE	0.018	0.017	0.008	0.016	0.017	0.006	0.012	0.012	0.005
	t-value	19.718	33.761	32.088	34.150	33.303	57.982	48.525	47.650	79.273
Time Dummy		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment Objective Dummy		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering		Month level	Month level	Month level	Month level	Month level	Month level	Month level	Month level	Month level
Observation		5743	5743	5743	5743	5743	5743	7286	7286	7286
R2 adj		13.04%	12.25%	14.32%	12.98%	12.17%	14.24%	13.42%	12.22%	15.69%

This table shows the regression of the monthly estimated coefficients of the determinants of fund´s fee, during the period from June 2009 to December 2015, of the form: $\boldsymbol{TER_{i,t} = \beta_0 + \gamma^{'} FundChar_{i,t-1} + \theta Sensitivity\ (S)_{i,t} + \lambda \overline{Y}_{i,t} + \varepsilon_{i,t}}$. The dependent variable $\boldsymbol{TER_{i,t}}$ (columns (1) and (2)) is the fund's total expense ratio for fund i. As robustness analysis we replace the independent variable TER by the Fee Rate (Advisory´s compensation fee) (column (3)) defined as the compensation rate paid by investor to the advisory fund on the basis of the current total asset of the fund. $\boldsymbol{FundChar_{i,t-1}}$ is a vector of lagged underlying portfolio fund´s characteristics that are likely to determine the fund´s compensation fees. $\boldsymbol{Sensitivity\ (S)_{i,t}}$ is the flow to performance-sensitivity of the fund's flows, which is determined of the form: $\boldsymbol{Sensitivity\ (S)_{i,t} = \widehat{\beta}_0 + \widehat{\beta}_1 * Age_{i,t-1} + \widehat{\beta}_2 * Q/MAX_{i,t-1}}$. $\boldsymbol{\overline{Y}_{i,t}}$ is the expected risk-adjusted performance before expenses measured according to the models employed in Chapter 5, and $\boldsymbol{\varepsilon_{i,t}}$ is the generic error term. The vector $\boldsymbol{FundChar_{i,t-1}}$ consider the following lagged variables that may influence the costs of operating a fund: Fund Size which is the natural log of fund total asset value; Family Fund Size which is the natural log of total asset value grouped by family of funds; Fund age which is the natural log of the number of years since the fund´s organization; Turnover which is the estimated variable regarding the lesser of fund purchases or sales divided by the total asset value; Volatility computed as the standard deviation of the fund´s monthly return during the last twelve months; Fund Flow which is the new money inflow computed as net inflow into the fund as a percentage of total assets. We include a dummy variable to identify the five funds' investment objective calculated under our empirical style categories computed in section 4.2.4 of this document. We also include month dummies in all regressions. The regression is estimated by pooled ordinary least squares (OLS). We report standard errors clustered by time (month). Adjusted R2 statistics are reported in percentage. $*$, $**$, $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The number of observations is reported in the last rows.

These results agree with the intuitive expectation that the value created for investors is a reflection of the fees charged because, by including variables such as, size, age, and turnover, among others, that are likely to determine operating costs and that are related to performance, the relationship between fees and performance remains positive and significant at the 1% level. In addition, these results support the argument that having competitive costs are associated with better performance after fees (Gil-Bazo et al. 2009)

In column 1 for all risk-adjusted performance models, we show the results of regressing the full model by including the risk-adjusted performance and flow-to-performance sensitivity factors. The results in the first group of columns (columns labeled benchmark Sharpe) show that the coefficient of performance sensitivity is negative for both TER (column 1) and fee rate (column 3) and statistically significant at the 1% level. This result is also consistent with the other two regression models and is statistically significant at the 1% level.

For the customized benchmark Sharpe model (first group of columns), the negative coefficient suggests an indirect relationship between performance sensitivity and fees. That is, investors that are highly sensitive to net performance are also sensitive to fees: an increase in performance sensitivity implies a decrease in fees. Funds with persistently better performance have lower performance-sensitive investors; thus, these funds charge higher fees and the performance after fees caused by the escalation in fees is translated to an increase in the flow of money for large funds. This negative relationship suggests that investment funds in Colombia might exploit a low elasticity of demand of fund performance to be able to increase their fees, as posited by Gil-Bazo et al. (2009). These results are consistent with the findings in Christoffersen and Musto (2002) and Gil-Bazo et al. (2009) and are extended for non-U.S. funds because these authors obtained a negative relationship between performance sensitivity and fees for U.S. money market and equity mutual funds, respectively.

An interesting result of our findings that is consistent with previous research (Gil-Bazo et al., 2009) is that the inclusion of performance sensitivity in our model does not affect the positive relationship between fees and risk-adjusted performance. In contrast, in column 2, the estimated coefficient of risk-adjusted performance—for which we have omitted performance sensitivity as a regressor—does not significantly change (0.009) and is statistically significant at the 1% level relative to the estimated coefficient (0.008) in column 1. Thus, elasticity of demand or performance sensitivity for investment funds in Colombia appears to be an important determinant of fees because the relationship is significant at the 1% level. However, this negative relationship cannot explain why badly performing investment funds in Colombia might charge higher fees.

The economic significance of these results is that an increase of one standard deviation in the risk-adjusted performance before fees is associated with an increase of 0.57 basis points in TER, as previously stated. In contrast, a one standard deviation increase in performance sensitivity is associated with a decrease of 3.81 basis points in TER. As was previously mentioned, performance sensitivity (or the elasticity of demand) contributes as a relevant factor in establishing the fees. To put into perspective all of these regression coefficients, we see (for the benchmark Sharpe model in the first group of columns) that an increase of one standard deviation in fund size, family size, turnover, volatility, and flows is associated with a decrease in TER of –3.94, –1.48, –0.19, –0.15, and –1.0 basis points, respectively. These results are significantly different from zero, except for volatility. A one standard deviation increase in fund age is associated with an increase in TER of 4.24 basis points and is significantly different from zero.

These results indicate that better fund performance is associated with higher fees, and this increase in performance is translated into investors. However, funds with worse performance before fees charge even higher fees. Larger investment funds, higher turnover, and higher money inflows are associated with lower fees. The same results are observed for the other two regression models. In these models, the relationships between fees and fund size, turnover, volatility, or flow are negative and significantly different from zero, whereas the relationship between fees and fund age is positive and significantly different from zero. This evidence supports the argument that economies of scale might reduce the fund's operating costs, which is associated with better performance (Gil-Bazo et al., 2009).

For the regression model under the benchmark prospectus and the selection return (second and third group of columns), the negative coefficient of the performance sensitivity still suggests an indirect relationship between investors' sensitivity to net performance and fees. This result is consistent with the result obtained using the benchmark Sharpe model, confirming a low elasticity of demand using these two regression models. However, using these two regression models, we also find support that the elasticity of demand or performance sensitivity for investment funds in Colombia appears to be an important determinant of fees. However, this relationship cannot explain by itself why funds with bad performance might have higher fees, given that the estimated coefficient of the risk-adjusted performance in column 2 does not change considerably compared with the estimated coefficient in column 1 and is statistically significantly different from zero.

In addition, the negative relationship between performance sensitivity and fees using the benchmark prospectus regression model support our argument that no conclusive evidence exists to argue that advisory companies in Colombia intentionally are interested in manipulating prospectuses or technical reports to present better results or more value added over the performance returns obtained. These findings also emphasize and support the need for better benchmark returns to evaluate fund performance and provide a more consistent view of investment decisions—the information provided by the advisory companies in their technical reports might not be as precise as investors need and is noisier.

8.3. Interpretation

To summarize our results, we still find that, on average, investment funds in Colombia have a positive relationship between risk-adjustment performance and fees, even though we include variables such as size, age, and turnover, among others. As posited by Gil-Bazo et al. (2009), these variables are probably important factors that explain operating costs related to performance.

Our results are also consistent with those of previous studies (Christoffersen and Musto's, 2002; Gil-Bazo et al. 2009) on fund flows for investment fund industries. We do not find evidence to support the concept that flows are positively related to past performance. However, we find that negative performance relative to the benchmark reduces flows, and relatively sophisticated investors in Colombia appear to penalize funds for poor performance (Sensoy, 2009). Moreover, we find evidence that flow-to-performance sensitivity decreases with fund age, and fund flow and flow-to-performance sensitivity increase with Q/MAX.

Our results extend the findings of Gil-Bazo et al. (2009) and Christoffersen and Musto (2002) for non-U.S. funds because, although our findings are obtained for smaller samples funds, we present evidence that the elasticity of demand or performance sensitivity for investment funds in Colombia is an important factor for establishing fees because investors that are highly sensitive to net performance are also sensitive to fees. Thus, if investors' performance sensitivity increases, they expect a decrease in fees.

Our finding are also consistent with previous research (Sensoy; 2009; Gil-Bazo et al., 2009; Huang, Wei, and Yan, 2007; Barber, Odean, and Zheng, 2005; Nanda, Wang, and Zheng, 2005; Jain and Wu, 2001; Sirri and Tufano, 1998; Chevalier and Ellison, 1997; Gruber, 1996; Ippolito, 1992). We present evidence that having low costs should be associated with better performance. Economies of scale might reduce the operating costs for larger funds; thus, we show that larger funds are associated with lower fees. Learning economies might reduce operating costs for older funds if the learning can be passed on to investors in the form of lower fees. In our results, we find no evidence for this argument because older funds are associated with higher fees. Higher expenses might be synonymous with larger investments in research tools and higher salaries for “more talented managers,” and we find evidence that average fund performance is still positively related to funds’ total expenses (Gil-Bazo et al. 2009). We do not find evidence to support the strategic argument posited by Christoffersen and Musto (2002) that funds with worse past performance charge higher fees because these higher fees are translated into increases in funds’ money flows.

The differences among the performance sensitivity coefficients for the three regression models might have arisen if our performance sensitivity measures are likely to contain substantial measurement errors. Given the limitations of our sample, we were not able to include measures of a convex relationship between performance and flows (Gil-Bazo et al., 2009) and a proxy for participation costs. Thus, this measurement, as posited by Gil-Bazo et al. (2009), may include errors that could affect the coefficient estimates. In addition, the cross-sectional variation in estimated performance might not reflect the true alpha.

Given the limitations of our sample, we were not able to assess for Colombian investment funds whether nonmarketing or marketing fees can explain a positive or negative relationship between performance and total fees. We also note that other possible options might exist to explain a relationship between performance and fees and that we explicitly did not consider in our research, such as marketing fees, better shareholder statements, and fund governance in the determination of fees, among others. Although we believe that the sample used for these investigations is the most comprehensive dataset ever prepared to study investment fund performance in Colombia in terms of number of funds and number of attributes, our data unfortunately do not allow us to prevent all of these limitations. Thus, we believe that the ability to explain our findings might be limited.

9. DETERMINANTS OF FUND PERFORMANCE

Finally, in this section, we investigate how fund characteristics might determine investment fund performance in Colombia from 2009 to 2015.

9.1. Empirical Methodology

To determine whether monthly fund performance, fund characteristics, and manager characteristics—when available—affect Colombian investment fund performance from 2009 to 2015, we regress a fund's risk-adjusted return on the compensation fee and set of control variables. The model specification is as follows:

$$\boldsymbol{Y_{i,t} = \alpha_0 + \beta CompensationFee_{i,t} + \gamma FundSize_{i,t} + \lambda FundChar_{i,t} +}$$
$$\boldsymbol{\varphi \mathrm{Manager} Char_{i,t} + \delta Y_{i,t-1} + \varepsilon_{i,j}} \quad (23)$$

where *i* indices investment funds at time t. $\boldsymbol{Y_{i,t}}$ is the fund's risk-adjusted return with respect to different models employed in chapter 5 to analyze investment fund performance. Following Ferreira et al. (2012) and Gil-Bazo et al. (2009), we want to study the relationship between before-fee risk-adjusted performance and fund characteristics. Hence, we replace the after-fee risk-adjusted measure $\boldsymbol{Y_{i,t}}$ with the before-fee equivalent. $\boldsymbol{CompensantionFee_{i,t}}$ is the fund's TER for fund *i* (Ferreira et al. 2012). The vector $\boldsymbol{FundSize_{i,t}}$ represents fund size, which is the natural log of total asset value, and family fund size is the natural log of a fund's total asset value grouped by fund family. The vector $\boldsymbol{FundChar_{i,t}}$ considers the following variables that might influence the determinants of performance: fund age, which is the natural log of the number of years since the fund's organization; turnover, which is the estimated variable regarding the lesser of fund purchases or sales divided by the total asset value; fund flow, which is the new money inflow computed as net inflow into the fund as a percentage of total assets, lagged by one period; account size, which is the natural log of the average number of investors in a fund; minimum investment, which is the natural log of the lowest minimum initial investment required to become an investor in a fund; and dummy variables to identify front loads, back loads, performance incentives, and open-end or closed-end funds. The vector $\boldsymbol{ManagerChar_{i,t}}$ considers the following variables to measure the management structure that might influence the performance determinants as in Ferreira et at. (2012): a dummy variable to identify whether the fund is managed by a team or a sub-advisory company; a dummy variable to identify whether the fund manager took postgraduate coursework or has a master's degree; and tenure, which is the natural log of the months of experience of a fund's manager. $\boldsymbol{Y_{i,t-1}}$ is the lagged fund's risk-adjusted return. In addition, $\boldsymbol{\varepsilon_{i,t}}$ is the generic error term. We include a dummy variable to identify the five funds' investment objective calculated under our empirical style categories computed in section 4.2.4. We also include month dummies in all regressions to account for cross-sectional dependence. The regression is estimated using the OLS method. We cluster the residuals using White's heteroskedasticity-robust standard error, and t-statistics are clustered at the fund and month levels to account for autocorrelation in fund and month performance.

We develop the aforementioned relationship following the methodology employed by Ferreira et at. (2012), which is also built on the literature on the determinants of mutual fund performance, such as Pollet and Wilson (2008); Yan (2008); Edelen, Evans, and Kadlec (2007); Chen et al. (2004); Berk and Green

(2004); Sapp and Tiwari (2004); Dahlquist et al. (2000); Stein (2002); Khorana and Servaes (1999); Zheng (1999); Carhart (1997); Gruber (1996); and Grinblatt and Titman (1989b, 1994).

These studies indicated that fund size is negatively related to fund performance because of economies of scale (Ferreira et al., 2012; Pollet and Wilson, 2008; Chen et al., 2004; Dahlquist et al., 2000). However, Ferreira et al. (2012) found that this result is different for mutual funds outside the United States. In this case, the relationship is positive because of the difference in size between U.S. and non-U.S. funds. Fund family size has a positive relationship with fund performance because, in this case, economies of scale and scope might generate a positive effect (Ferreira et al., 2012; Chen et al., 2004; Khorana and Servaes, 1999). Regarding fund age, the effect on performance has mixed effects. For instance, Chen et al. (2004) and Ferreira et al. (2012) found no relationship between the age and performance of U.S. mutual funds. However, Ferreira et al. (2012) found that, outside the United States, newer mutual funds seem to perform better than older mutual funds. The effect on the performance of front-load versus back-load fees also has mixed effects. Some authors found no relationship between performance and loads (Chen et al., 2004; Ferreira et al., 2012), whereas others found a negative relationship (Carhart, 1997; Pollet and Wilson, 2008). The flow of new money into and out of mutual funds follows the predictor of future performance. Some authors found that fund flows have a positive relationship (Gruber, 1996; Zheng, 1999), whereas others, such as Ferreira et al. (2012), found no evidence of a relationship between flows and performance for U.S. funds but, in contrast, found such evidence for non-U.S. funds. Thus, funds that receive more new money perform better than those that receive less new money, indicating a smart money effect. Regarding managers' structure and performance, prior studies found that funds managed by one manager have a positive relationship with performance as opposed to funds managed by many managers (Stein, 2002; Chen et al., 2004; Massa, Reuter, and Zitzewitz, 2010; Ferreira et al., 2012). In turn, evidence exists that manager's education and tenure have a positive relationship with U.S. mutual fund performance because a long tenure may imply greater job security and, hence, less short-term behavior by the manager; moreover, higher education might be related to the quality of the investment decisions and the efficient operation of funds managed by talented managers (Golec, 1996; Chevalier and Ellison, 1999; Gil-Bazo et al., 2009).

9.2. Empirical Results

Table 26 shows the results of fund performance determinants for the OLS regression estimated in Equation (23). We estimated funds' determinant performance using the three risk-adjusted performance models computed in chapter 5. Table 26 provides the following: i) in the first column, the fund's performance determinants using the customized benchmark Sharpe portfolio weights (columns called Benchmark Sharpe); ii) in the second column, the fund's performance determinants using the approximated benchmark prospectuses' portfolio weights (columns called Benchmark Prospectus); and iii) in the third column, the fund's performance determinants using the selection return (column called Selection Return). We use $\boldsymbol{Y_{i,t}}$ as a dependent variable, which is the monthly risk-adjusted performance for fund *i*. We report robust standard errors clustered by time for all OLS regressions because the standard errors clustered by White and time*x*fund slightly change the White standard error.

Table 26: Determinants of fund´s performance according to different regression models defined in Chapter 5.

Variable		Benchmark Sharpe (1)	Benchmark Prospectus (2)	Selection Return (3)
Ln, Fund Total Asset	Coef	0.037 ***	0.043 ***	0.020 ***
	SE	0.007	0.009	0.004
	t-value	5.355	4.769	4.852
Ln, Family Total Asset	Coef	-0.033 **	-0.028 *	-0.046 ***
	SE	0.014	0.015	0.011
	t-value	-2.274	-1.920	-4.312
Ln, Fund Age	Coef	-0.005	-0.009	0.025 *
	SE	0.022	0.023	0.015
	t-value	-0.230	-0.372	1.680
TER	Coef	0.294 ***	0.247 ***	0.194 **
	SE	0.059	0.092	0.077
	t-value	4.960	2.690	2.504
Turnover	Coef	-0.041 **	-0.017	-0.030 ***
	SE	0.020	0.018	0.008
	t-value	-2.053	-0.972	-3.898
Alpha: Risk-Adjusted Return (t-1)	Coef	0.105	0.074	0.094
	SE	0.083	0.069	0.069
	t-value	1.265	1.071	1.366
Fund Flow (t-1)	Coef	0.003	-0.030	0.010 ***
	SE	0.021	0.025	0.003
	t-value	0.119	-1.187	3.641
Ln, Min Invesment	Coef	-0.002	-0.003	-0.003
	SE	0.004	0.004	0.003
	t-value	-0.568	-0.762	-1.199
Ln, Account Size	Coef	0.021 **	0.021 ***	0.027 ***
	SE	0.009	0.008	0.008
	t-value	2.434	2.738	3.389
Open_Closed Dummy	Coef	-0.380 ***	-0.384	-0.227 ***
	SE	0.091	0.240	0.078
	t-value	-4.195	-1.603	-2.916
Front_load Dummy	Coef	-0.016	-0.076	-0.225
	SE	0.430	0.408	0.227
	t-value	-0.037	-0.186	-0.990
Back_load Dummy	Coef	0.133 ***	0.156 ***	0.131 ***
	SE	0.028	0.027	0.022
	t-value	4.782	5.855	6.043
Performance Incentive Dummy	Coef	0.021	0.030	0.016
	SE	0.017	0.023	0.019
	t-value	1.267	1.333	0.821
Sub-Advisory Management Fund	Coef	0.291	0.301	0.246
	SE	0.223	0.226	0.245
	t-value	1.307	1.335	1.002
Manager Postgraduate Cert dummy	Coef	-0.026	0.013	0.002
	SE	0.022	0.018	0.021
	t-value	-1.186	0.711	0.115
Manager Master Education dummy	Coef	0.036	0.071 **	0.053 **
	SE	0.028	0.032	0.023
	t-value	1.313	2.201	2.303
Tenure manager	Coef	0.013	-0.033	-0.003
	SE	0.018	0.036	0.022
	t-value	0.694	-0.922	-0.146
Intercept	Coef	0.249	0.058	0.409
	SE	0.275	0.427	0.268
	t-value	0.905	0.136	1.530
Time Dummy		Yes	Yes	Yes
Investment Objective Dummy		Yes	Yes	Yes
Clustering		Month level	Month level	Month level
Observation		5792	5792	8705
R2 adj		4.82%	4.90%	3.70%

This table shows the regression of the monthly estimated coefficients of the determinants of fund´s performance, during the period from June 2009 to December 2015, of the form: $Y_{i,t} = \alpha_0 + \beta CompensationFee_{i,t} + \gamma FundSize_{i,t} + \lambda FundChar_{i,t} + \varphi \mathbf{Manager}Char_{i,t} + \delta Y_{i,t-1} + \varepsilon_{i,j}$. $Y_{i,t}$ is the fund´s risk-adjusted return with respect to different models employed in chapter 5 to analyze investment fund performance. Following Ferreira et al. (2012) and Gil-Bazo et al. (2009) we want to study the relation between before-fee risk-adjusted performance and fund characteristics. Hence, we will replace the after-fee risk-adjusted measure $Y_{i,t}$ with the before fee equivalent. $CompensantionFee_{i,t}$ is the fund's total expense ratio (TER) for fund *i*. The vector $FundSize_{i,t}$ consider the following variables: Fund Size which is the natural log of fund total asset value; Family Fund Size which is the natural log of total asset value grouped by family of funds. The vector $FundChar_{i,t-1}$ consider the following variables that might influence the performance determinants: Fund age which is the natural log of the number of years since the fund´s organization; Turnover which is the estimated variable regarding the lesser of fund purchases or sales divided by the total asset value; Fund Flow which is the new money inflow computed as net inflow into the fund as a percentage of total assets; Account Size which is the natural log of the average number of investors in a fund; Minimum investment which is the natural log of the lowest minimum initial investment required to become an investor in a fund; dummy variables to identify front loads, back loads, performance incentives and open-end or close-end funds. The vector $ManagerChar_{i,t}$ consider the following variables to measure the management structure that might influence the performance determinants, following Ferreira et at. (2012): Dummy variable to identify if the fund is managed by a team or a Sub Advisory Company; Dummy variable to identify if the fund´s manager has a postgraduate course or master degree; Tenure which is the natural log of months of experience of fund´s manager. $Y_{i,t-1}$ is the lagged fund´s risk-adjusted return. And $\varepsilon_{i,t}$ is the generic error term. We include a dummy variable to identify the five funds' investment objective calculated under our empirical style categories computed in section 4.2.4 of this document. We also include month dummies in all regressions. The regression is estimated by pooled ordinary least squares (OLS). We report standard errors clustered by time (month). Adjusted R2 statistics are reported in percentage. $*$, $**$, $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The number of observations is reported in the last rows.

9.2.1. Size and Performance

As indicated in Table 26 for all risk-adjusted performance models, the coefficient for fund size is, on average, positive and significant at the 1% level. If we consider the coefficient of fund size in the first column (Benchmark Sharpe), we might state that a one-standard deviation increase in fund size (the standard deviation of the log of total assets is 2.02) is related to an escalation in performance of 7.4 basis points per month. This effect has economic significance because the average of the fund performance is negative (–2 basis points). Our result is consistent with the findings obtained by Ferreira et al. (2002) for non-U.S. funds. These authors found that fund size is negatively related to fund performance in a sample of U.S. funds and is positively related in a sample of non-U.S. funds. Ferreira et al. (2012) posited that the positive relationship between size and performance for funds outside the United States, such as in Colombia, is explained because non-U.S. funds are smaller than U.S. funds. Hence, larger funds such as U.S. funds might face problems and challenges.

Larger funds might have several advantages over small funds, such as economies of scale from spreading expenses over more assets, the ability to negotiate better spreads through larger positions and trading volumes (Ferreira et al. 2002), better investment opportunities that might not available in smaller funds, and having more resources for research (Brennan and Hughes, 1991). However, larger funds might face problems and challenges because scalability is a determinant performance factor (Gruber, 1996; Berk and Green, 2004). Gruber (1996) and Berk and Green (2004) showed that managers of small funds can focus on a few investment opportunities that add value to investors, whereas managerial skills in larger funds might be "diluted" because of the pressure to continue to find good investment opportunities, implying diseconomies of scale (Ferreira et al., 2012). Larger funds face the liquidity constraint hypotheses, as posited by Chan et al. (2004), because managers must "trade high volumes of securities, attracting the attention of other market participants, suffering higher price impact costs" (Ferreira et al., 2012: page 18). Moreover, as posited by Cremers and Petajisto (2009), larger funds are less active than small funds because larger funds are close to index funds. Finally, Ferreira et al. (2012) indicated that when a fund approaches a certain size, economies of scale are "exhausted" for those large funds. They implied a negative relationship between size and performance and showed this relationship for funds in the United States, which are much larger than funds outside the United States. Thus, our findings support these arguments because, clearly, Colombian investment funds are much smaller than U.S. funds.

Conversely, we find that family size has a negative relationship with size and performance for all risk-adjusted performance models. Funds that perform better are more likely to be managed by a smaller company because family size has a negative effect on performance. The effect of family size is statistically significant at the 5%, 10%, and 1% levels, respectively. In addition, the effect is economically significant. The coefficient of family size in the first column (Benchmark Sharpe) indicates that a one-standard deviation increase in family fund size (the standard deviation of the log of family size of total assets is 1.52) is related to a decrease in performance of 5.0 basis points per month. This finding still supports the previously mentioned arguments because the ability to scale investments in larger funds is a limitation (Gruber, 1996; Berk and Green, 2004). Moreover, as posited by Ferreira et al. (2012), economies of scale are "exhausted" when a fund approaches a certain size. Our results extend the findings of Ferreira et al. (2012) for the determinants of a fund's performance outside the United States.

In Table 27, we re-estimate Equation (23) and group the fund performance determinates based on our empirical style classification from chapter 4. As Table (27) shows, the coefficients for fund size for all clusters are positive in most cases and significant in all regression models for cluster 2 (money market funds) and cluster 3 (debt funds)—these two clusters represent approximately 86% of the total funds analyzed. We find significant evidence that the size of the money market and debt funds in Colombia are associated with an increase in performance; thus, these funds can focus on investment opportunities that add value to investors. For funds classified in cluster 1 (equity funds), the coefficient is negative but not significant when we use the benchmark determined based on Carhart (1997). The results obtained for the other clusters are also not significant.

Table 27: Determinants of fund´s performance according to different regression models defined in Chapter 5, grouped by our Empirical Style Classification Algorithm.

Variable		Benchmark Sharpe					Benchmark Carhart	Benchmark Prospectus					Selection Return				
		Cluster 1 - Equity	Cluster 2 - Money Market	Cluter 3 - Debt	Cluster 4 - Balanced	Cluster 5 - Income	Cluster 1 - Equity	Cluster 1 - Equity	Cluster 2 - Money Market	Cluter 3 - Debt	Cluster 4 - Balanced	Cluster 5 - Income	Cluster 1 - Equity	Cluster 2 - Money Market	Cluter 3 - Debt	Cluster 4 - Balanced	Cluster 5 - Income
Ln, Fund Total Asset	Coef	0.124	0.003 **	0.056 ***	0.039	0.057	-0.035	0.138	0.011 **	0.059 ***	-0.031	0.111	-0.068	-0.003 *	0.035 **	0.104 **	-0.061
	SE	0.286	0.001	0.018	0.079	0.193	0.235	0.269	0.005	0.023	0.044	0.243	0.123	0.002	0.014	0.047	0.197
	t-value	0.434	2.379	3.160	0.497	0.297	-0.147	0.514	2.261	2.604	-0.703	0.457	-0.553	-1.796	2.478	2.219	-0.309
Ln, Family Total Asset	Coef	0.035	0.005	-0.002	0.531 *	-0.701	0.183	0.062	0.016 *	0.011	0.213	-1.010	-0.329 *	0.003	-0.016	0.219	-0.433
	SE	0.222	0.004	0.022	0.287	0.547	0.274	0.224	0.009	0.023	0.404	0.761	0.196	0.004	0.029	0.234	0.475
	t-value	0.158	1.116	-0.099	1.847	-1.281	0.668	0.276	1.858	0.484	0.528	-1.328	-1.680	0.758	-0.556	0.936	-0.911
Ln, Fund Age	Coef	0.994 *	-0.036 ***	0.202 ***	-1.197	5.556	2.095 ***	1.058 *	-0.062 ***	0.159 *	-0.474	7.008	0.522	-0.025 ***	0.127	-1.156 *	13.540 ***
	SE	0.568	0.010	0.076	0.908	3.811	0.545	0.563	0.017	0.089	1.198	4.702	0.512	0.008	0.078	0.643	3.879
	t-value	1.751	-3.541	2.641	-1.318	1.458	3.843	1.880	-3.752	1.782	-0.395	1.490	1.020	-3.171	1.635	-1.796	3.490
TER	Coef	0.286	0.185 **	0.149	-4.510 **	-4.710 ***	-0.574	0.328	0.258 ***	0.011	-1.941	-6.713 ***	-0.418	0.167 *	0.181	-0.800	-6.359 **
	SE	0.586	0.091	0.175	2.288	0.733	1.038	0.619	0.099	0.242	2.425	1.675	0.611	0.089	0.133	2.023	2.585
	t-value	0.488	2.036	0.855	-1.971	-6.429	-0.553	0.530	2.616	0.044	-0.800	-4.008	-0.684	1.882	1.359	-0.395	-2.460
Turnover	Coef	-2.615	-0.010 ***	-0.026	1.998	-0.835	-1.407	-2.345	0.009	0.061	1.723 *	-0.329	-2.369	-0.012 ***	0.168	-0.486	-3.628 ***
	SE	6.178	0.003	0.125	1.457	1.401	4.920	6.131	0.007	0.187	0.885	1.342	3.464	0.002	0.147	0.326	1.344
	t-value	-0.423	-3.272	-0.208	1.371	-0.596	-0.286	-0.383	1.251	0.327	1.947	-0.245	-0.684	-6.533	1.144	-1.490	-2.700
Alpha: Risk-Adjusted Return (t-1)	Coef	-0.006	0.367 **	-0.096	0.075	-0.204	-0.091	-0.010	0.089	-0.028	-0.043	-0.202	-0.005	0.388 ***	-0.029	-0.066	-0.061
	SE	0.100	0.150	0.097	0.131	0.125	0.143	0.098	0.121	0.090	0.163	0.137	0.088	0.117	0.053	0.168	0.078
	t-value	-0.064	2.444	-0.990	0.571	-1.634	-0.640	-0.100	0.737	-0.314	-0.265	-1.473	-0.056	3.315	-0.551	-0.395	-0.785
Fund Flow (t-1)	Coef	-0.374	-0.020	0.283 ***	0.451 ***	1.150	-1.698	-0.371	-0.045 **	0.188	0.243	0.462	0.095	-0.011 **	0.008	-0.035	0.529
	SE	3.136	0.015	0.068	0.149	0.777	3.615	3.131	0.023	0.123	0.201	0.777	0.060	0.005	0.005	0.138	0.815
	t-value	-0.119	-1.307	4.146	3.033	1.479	-0.470	-0.118	-2.005	1.522	1.211	0.594	1.589	-2.250	1.632	-0.254	0.649
Ln, Min Invesment	Coef	0.022	0.004 ***	-0.018 **	0.691	-0.479	-0.092	0.023	0.005 ***	-0.014	0.132	-0.422	-0.098	0.004 ***	0.014 **	1.652	-0.785
	SE	0.131	0.001	0.008	1.239	0.721	0.114	0.124	0.002	0.011	1.350	0.914	0.069	0.001	0.006	1.061	1.063
	t-value	0.170	3.504	-2.342	0.557	-0.664	-0.809	0.185	2.844	-1.322	0.098	-0.462	-1.417	3.798	2.287	1.557	-0.739
Ln, Account Size	Coef	0.272	-0.002	0.060 **	0.018	-0.136	0.858 **	0.266	-0.005	0.056 *	0.070	-0.285	0.302 *	0.003	0.021	-0.152 ***	0.121
	SE	0.237	0.002	0.024	0.086	0.437	0.363	0.228	0.004	0.030	0.075	0.510	0.172	0.003	0.019	0.055	0.334
	t-value	1.148	-0.795	2.567	0.215	-0.311	2.362	1.164	-1.175	1.874	0.932	-0.559	1.757	1.233	1.109	-2.765	0.362
Open_Closed Dummy	Coef	Omitted	-0.227 ***	-0.637 *	Omitted	Omitted	Omitted	Omitted	-0.581 **	0.375 **	Omitted	Omitted	Omitted	-0.242 ***	-0.071	Omitted	Omitted
	SE		0.074	0.335					0.290	0.191				0.057	0.218		
	t-value		-3.083	-1.900					-2.007	1.964				-4.253	-0.326		
Front_load Dummy	Coef	Omitted	0.260	-1.429 ***	Omitted	Omitted	Omitted	Omitted	0.076	-0.430	Omitted	Omitted	Omitted	-0.245	-1.379 ***	Omitted	Omitted
	SE		0.588	0.495					0.491	0.383				0.227	0.324		
	t-value		0.442	-2.883					0.154	-1.122				-1.075	-4.249		
Back_load Dummy	Coef	0.081	0.032 ***	-0.058 *	-0.293	Omitted	-0.501	0.084	0.062 ***	0.060	-0.435	Omitted	-1.197 *	0.029 **	0.073	-0.454 *	Omitted
	SE	1.190	0.011	0.032	0.433		1.057	1.152	0.015	0.090	0.405		0.643	0.013	0.045	0.256	
	t-value	0.068	2.982	-1.839	-0.676		-0.474	0.073	4.052	0.672	-1.072		-1.862	2.315	1.625	-1.771	
Performance Incentive Dummy	Coef	Omitted	0.019	0.271 ***	Omitted	Omitted	Omitted	Omitted	0.029	0.232 ***	Omitted	Omitted	Omitted	0.011	0.111 *	Omitted	Omitted
	SE		0.018	0.078					0.020	0.085				0.012	0.065		
	t-value		1.081	3.472					1.434	2.738				0.898	1.711		
Sub-Advisory Management Fund	Coef	0.418	Omitted	Omitted	Omitted	Omitted	0.507	0.423	Omitted	Omitted	Omitted	Omitted	0.861	Omitted	Omitted	Omitted	Omitted
	SE	0.569					1.266	0.557					0.687				
	t-value	0.735					0.400	0.758					1.253				
Manager Postgraduate Cert dummy	Coef	-0.283	-0.036 ***	-0.008	0.030	0.189	0.119	-0.361	-0.007	-0.080	0.016	0.191	0.240	-0.041 ***	-0.122 ***	0.027	0.625
	SE	0.482	0.013	0.035	0.140	0.328	0.641	0.458	0.025	0.052	0.152	0.363	0.280	0.013	0.044	0.136	0.484
	t-value	-0.586	-2.778	-0.236	0.214	0.576	0.185	-0.787	-0.279	-1.533	0.104	0.526	0.857	-3.193	-2.784	0.195	1.292
Manager Master Education dummy	Coef	-0.436 *	-0.029 **	0.085 *	0.017	Omitted	-1.585 **	-0.451 *	-0.009	0.060	0.041	Omitted	0.262	-0.036 ***	-0.026	0.116	-0.637
	SE	0.228	0.014	0.047	0.107		0.671	0.240	0.032	0.059	0.102		0.326	0.012	0.082	0.108	1.130
	t-value	-1.908	-2.141	1.792	0.162		-2.364	-1.877	-0.284	1.021	0.404		0.804	-2.888	-0.316	1.076	-0.564
Tenure manager	Coef	0.150	0.028 **	-0.007 *	0.228	Omitted	0.586	0.118	-0.002	-0.088	-0.077	Omitted	0.155	0.027 **	0.051	0.215	4.672 **
	SE	0.251	0.011	0.004	0.407		0.379	0.260	0.023	0.089	0.377		0.263	0.012	0.058	0.388	2.191
	t-value	0.598	2.527	-1.683	0.559		1.545	0.453	-0.068	-0.984	-0.205		0.588	2.189	0.894	0.554	2.132
Intercept	Coef	-6.762	0.158	-0.832 **	-12.869	-12.000	-17.597 ***	-7.413	0.186	-1.788 ***	-2.716	-16.020	3.897	0.197 **	-1.010 *	-22.194	-75.377 **
	SE	4.813	0.133	0.420	17.519	9.658	5.677	4.735	0.348	0.531	19.266	11.546	2.783	0.099	0.561	15.746	33.798
	t-value	-1.405	1.192	-1.982	-0.735	-1.242	-3.100	-1.566	0.533	-3.370	-0.141	-1.388	1.401	2.001	-1.802	-1.410	-2.230
Time Dummy		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering		Month level	Month level	Month level	Month level	Month level	Month level	Month level	Month level	Month level	Month level	Month level	Month level	Month level	Month level	Month level	Month level
Observation		416	4344	731	174	127	416	416	4344	731	174	127	692	6404	1106	304	199
R2 adj		10.75%	30.09%	25.93%	5.81%	22.44%	28.54%	11.12%	15.16%	20.13%	17.78%	24.32%	10.64%	31.10%	11.72%	2.19%	17.02%

This table shows the regression of the monthly estimated coefficients of the determinants of fund´s performance grouped by our Empirical Style Classification Algorithm employed in chapter 4, during the period from June 2009 to December 2015, of the form: $\boldsymbol{Y_{i,t} = \alpha_0 +}$

$\boldsymbol{\beta} \boldsymbol{CompensationFee}_{i,t} + \boldsymbol{\gamma} \boldsymbol{FundSize}_{i,t} + \boldsymbol{\lambda} \boldsymbol{FundChar}_{i,t} + \boldsymbol{\varphi}\mathbf{Manager}\boldsymbol{Char}_{i,t} + \boldsymbol{\delta} \boldsymbol{Y}_{i,t-1} + \boldsymbol{\varepsilon}_{i,j}$. $\boldsymbol{Y}_{i,t}$ is the fund´s risk-adjusted return with respect to different models employed in chapter 5 to analyze investment fund performance. $\boldsymbol{CompensantionFee}_{i,t}$ is the fund's total expense ratio (TER) for fund *i*. The vector $\boldsymbol{FundSize}_{i,t}$ considers the following variables: Fund Size which is the natural log of fund total asset value; Family Fund Size which is the natural log of total asset value grouped by family of funds. The vector $\boldsymbol{FundChar}_{i,t-1}$ consider the following variables that might influence the performance determinants: Fund age which is the natural log of the number of years since the fund´s organization; Turnover which is the estimated variable regarding the lesser of fund purchases or sales divided by the total asset value; Fund Flow which is the new money inflow computed as net inflow into the fund as a percentage of total assets; Account Size which is the natural log of the average number of investors in a fund; Minimum investment which is the natural log of the lowest minimum initial investment required to become an investor in a fund; dummy variables to identify front loads, back loads, performance incentives and open-end or close-end funds. The vector $\boldsymbol{ManagerChar}_{i,t}$ consider the following variables to measure the management structure that might influence the performance determinants, following Ferreira et at. (2012): Dummy variable to identify if the fund is managed by a team or a Sub Advisory Company; Dummy variable to identify if the fund´s manager has a postgraduate course or master degree; Tenure which is the natural log of months of experience of fund´s manager. $\boldsymbol{Y}_{i,t-1}$ is the lagged fund´s risk-adjusted return. And $\boldsymbol{\varepsilon}_{i,t}$ is the generic error term. We include a dummy variable to identify the five funds' investment objective calculated under our empirical style categories computed in section 4.2.4 of this document. We also include month dummies in all regressions. The regression is estimated by pooled ordinary least squares (OLS). We report standard errors clustered by time (month). Adjusted R2 statistics are reported in percentage. $*$, $**$, $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The number of observations is reported in the last rows.

9.2.2. Age and Performance

We find that the relationship between age and performance is negative for the benchmark Sharpe and prospectus regression models, and positive for the selection return model. These findings are statistically significant at the 10% level only in the case of the selection return model. In the other two regression models, the relationship is not significant. These findings are consistent with the evidence in Ferreira et al. (2012) and Chen et al. (2004), who found a nonsignificant negative relationship between performance and age, suggesting that younger funds perform better than older funds. If we consider the coefficient of age in the first column (Benchmark Sharpe), we might state that a one-standard deviation increase in age (the standard deviation of the log of age is 0.74) is associated with a decrease in performance of 0.37 basis points per month. In this sense, arguments exist that younger funds are more responsive and dedicated to obtaining better fund performance to survive and be sustainable. However, contrasting arguments state that older funds tend to perform better than younger funds because the latter might reflect higher costs and lack of experience during the setup phase (Ferreira et at., 2012).

Table 27, which reflects a re-estimation of Equation (23) and groups the results based on our empirical style classification, shows that the relationship between age and performance runs in both directions—it is positive for equity funds (cluster 1) and debt funds (cluster 3) and negative for money market funds (cluster 2). These relationships are significant for all regression models. These results reflect the statement that older equity and debt funds perform better than younger funds, whereas younger money market funds perform better than older funds. Our evidence suggests that youth might be a disadvantage for equity and debt funds at the time of an investment decision because younger funds suffer from a lack of experience and might have higher costs that erode performance (Ferreira et al., 2012). Conversely, the longevity of money market funds is not an advantage: newer funds perform better than older funds because—and as posited by Ferreira et al. (2012)—younger funds need to act more responsively and be devoted to performance to survive. For the other clusters of funds, we find a statistically nonsignificant negative or positive relationship between age and performance.

9.2.3. Total expenses and Performance

We find a positive relationship between performance and TER. This result is consistent with our univariate regression model in chapter 6. Because our relationship is statically significant, if we consider the coefficient of TER in the first column (Benchmark Sharpe), we might state that a one-standard deviation increase in TER (the standard deviation of TER is 0.12) is related to a performance increase of 3.61 basis points per month. Our results extend the finance literature on investment fund performance because our empirical evidence suggests that the relationship between fees and investment fund performance is mixed. For example, Ferreira et al. (2012), Khorana et al. (2009), and Gil-Bazo et al. (2009) found a negative relationship between fees and performance in U.S. funds; in European funds, Dahlquist et al. (2000), Otten and Bams (2002) found evidence of this negative relationship, but Chen et al. (2004) found no such relationship. Our evidence of this positive relationship complements the previous investment fund literature and, as stated in chapter 6, agrees with the intuitive expectation that the value that funds create for investors is a reflection of fees charged because, in our case, funds that charge higher fees have better performance before expenses but worse performance after expenses.

In Table 27, in which we re-estimated Equation (23) to group the results based on our empirical style classification, we observe a mixed effect by investment objective, which is consistent with our results obtained in Chapter 6. The first group of columns called Benchmark Sharpe shows that a positive relationship exists between performance before fee and fund fee for Clusters 1, 2, and

3, but a negative relationship for clusters 4 and 5. These relationships are statistically significant for clusters 2, 4, and 5 at the 5%, 5%, and 1% levels, respectively. The empirical evidence suggests that cluster 2 (money market funds), which represents more than two-thirds of the sample, performs better by having higher fees. However, as stated in chapter 6, such excess fees are not high enough to fully compensate for the differences in fund performance after fees. A one-standard deviation increase in TER (the standard deviation of TER is 0.12% or 12 basis points) is related to a performance increase before fees of 2.3 basis points per month. Conversely, the evidence suggests that cluster 4 (balanced funds) and cluster 5 (income funds) perform worse by having higher fees. A one-standard deviation increase in TER (the standard deviation of TER is 0.12%, or 12 basis points) is associated with a decrease in performance before fees of –55.4 basis points and –58 basis points per month, respectively, suggesting that performance after fees is even worse. Regarding cluster 1 (equity funds) and cluster 3 (debt funds), we find that the relationship between performance before fee and TER is not statistically significant. These findings are consistent with the results obtained in the other three regression models in Table 27—Prospectus Benchmark, Selection Return, and Carhart for equity funds (cluster 1).

9.2.4. Loads and Performance

In addition to TER, investment funds usually charge front-end loads (at the time of purchasing securities) or back-end loads (at the time of redeeming securities). As posited by Ferreira et al. (2002), the purpose of the back-end load is to discourage redemption. Investment funds intend to dissuade investors from redeeming securities by making them more expensive; thus, they are able to invest in riskier portfolios to obtain better performing results. The empirical evidence confirms this statement. As posited by Chordia (1996), loads dissuade redemption in open-end funds because the funds hold more cash when investors perceive uncertainty about redeeming their securities. Our results support this evidence. We find that back-end load funds are positively related to performance, and this positive relationship is statistically significant at the 1% level for all regression models. Our results are economically significant because a one-standard deviation increase in back-end load funds (the standard deviation back-end loads is 0.47) is related to a performance increase of 6.23 basis points per month (under the benchmark Sharpe regression model). Our findings extend the finance literature on investment funds because previous studies, such as Ferreira et al. (2012), Chen et al. (2004), Pollet and Wilson (2008), and Carhart (1997), found either no relationship or a negative relationship between back-end load and performance. In terms of performance incentives, we find a positive but not statistically significant relationship with performance.

However, we find that funds that charge loads at the time of purchasing securities (front-end loads) have a negative relationship with performance. Although this negative relationship is not statistically significant, its economic impact is also not significant because a one-standard deviation increase in funds with front-end loads (the standard deviation of front-end loads is 0.2) is related to a decrease in performance of 0.32 basis points per month (under the benchmark Sharpe regression model).

In Table 27, in which Equation (23) is re-estimated, we group the results based on our empirical style classification and find that the relationship between back-end load fees and performance run in different directions. Money market funds (cluster 2) with back-end loads are positively related to performance, and this positive relationship is statistically significant at the 1% and 5% levels for the three regression models. This empirical evidence confirms that, for money market funds with back-end loads, this condition dissuades redemption and acts in favor of performance because managers might hold more cash to invest in securities. A one-standard deviation increase in money market funds with back-end loads (the standard deviation of back-end loads is 0.47) is related to a performance increase of 1.5 basis points per month (under the benchmark Sharpe regression model). Conversely, we find that debt funds (cluster 3) with back-end loads are negatively related to performance, and this relationship is statistically significant at the 10% level for the benchmark Sharpe regression models. In the other two regression models, the relationship is not statically significant. This empirical evidence confirms that, for debt funds with back-end loads, dissuading redemption does not act in favor of fund performance. A one-standard deviation increase in debt funds with back-end loads (the standard deviation of back-end loads is 0.47) is related to a performance decrease of –2.7 basis points per month (under the benchmark Sharpe regression model). For clusters 1 (equity funds), 4 (balanced funds), and 5 (income funds), we find no statically significant relationship for the benchmark Sharpe, benchmark prospectus, and Carhart (1997) regression models. However, for the selection return regression model, we find that a negative relationship exists for clusters 1 (equity funds) and 4 (balanced funds) between back-end load and performance, and this relationship is statically significant at the 10% level.

9.2.5. Open-end funds vs. Closed-end funds and Performance

Given that more than 94% of our sample is represented by open-end funds, we find an interesting result when we observe the number of open-end and closed-end funds. Our results suggest that advisors in open-end funds are negatively related to performance and that this negative relationship is statistically significant at the 1% level for the benchmark Sharpe and selection return regression models. These results are economically significant because a one-standard deviation increase in open-end funds (the standard deviation of open-end funds is 0.24) is associated with a decrease in performance of 9.0 basis points per month (under the benchmark Sharpe regression model), and the average performance of the investment funds in Colombia under the Benchmark Sharpe and Selection Return is –2.0 basis points and –1.3 basis points, respectively. Our findings are consistent with previous research because a fund manager for closed-end funds and not open-end funds usually cannot issue more securities to expand the fund's portfolio. Thus, a fund manager in a closed-end fund can increase total assets, and his compensation is only tied to positive investment performance (Coles et al., 2000; Khorana et al., 1999).

These findings are also consistent when we analyze this relationship by grouping the results based on our empirical style classification in Table 27. We find that in most of the clusters, open-end funds are negatively related to performance, and this negative relationship is statistically significant.

9.2.6. Fund flows and Performance

Regarding fund flows, we find a positive relationship between fund flows and subsequent fund performance under the Benchmark Sharpe and Selection

Return regression models. This relationship is statistically significant only under the selection return model. These results support the smart money hypothesis of Gruber (1996), which states that investors can detect skilled managers and direct their money to them. The flow of new money into and out of mutual funds follows the predictor of future performance (Gruber, 1996; Zheng, 1999). Using the coefficients in columns 1 and 3, a one-standard deviation increase in flows is related to an increase in subsequent performance of 0.30 and 1.23 basis points per month, respectively. Our results extend the evidence found in Ferreira et al. (2012) for non-U.S. funds, which indicate that investors might identify talented fund managers outside the United States. In contrast, the results obtained under the Benchmark prospectus regression model show that the relationship is negative and not statistically significant. Although this result is completely different from those obtained by the other two regression models, in our opinion this finding supports our hypothesis that the information provided by investors is not accurate and is noisier. Recall that the benchmark prospectus model is constructed based on the portfolio weights described in technical reports issued by company advisories.

To test whether these results are robust, we checked for the presence of a serial correlation between the independent and dependent variables that might inflate or impact the t-statistics on the dependent variable, thereby biasing us toward accepting the presence of a significant relationship between two variables. Ferson et al. (2003) posited that the first-level of autocorrelation between dependent and independent variables in performance regressions may lead to erroneous conclusions when the results of the autocorrelation are higher than

90% and when the R^2 statistics in the regression model are less than 1%. In our case, the average autocorrelation of fund flows is 0.24 and 0.20 for the benchmark Sharpe performance and the selection return, respectively. However, the autocorrelation with the benchmark prospectus performance is –0.70. In addition, the adjusted R^2 statistics are 4.8% and 3.7% for the benchmark Sharpe and selection return regression models, respectively, and 4.9% for the benchmark prospectus regression model. This result suggests that the erroneous conclusion problem previously described might not be a problem in our data set.

Alternatively, in Table 27, which provides the re-estimated Equation (23) and groups the results based on our empirical style classification, we observe that for the benchmark Sharpe model, the relationship between fund flows and subsequent fund performance for clusters 3 (debt funds), 4 (balanced funds), and 5 (income funds) is positive and is significant at any level only for clusters 3 and 4. This result is consistent with the smart money hypothesis of Gruber (1996). For the rest of the regression models, we find no statistically significant relationship between fund flows and subsequent fund performance for these three clusters. However, the result is different for clusters 1 (equity funds) and 2 (money market funds). For cluster 1, we find a nonsignificant negative relationship between fund flows and subsequent fund performance in all regression models, but a significant relationship in cluster 2 only for the prospectus benchmark and selection return regression models. This negative relationship shows that equity and money market funds experiencing net inflows during the last month performed worse than funds that experienced outflows.

9.2.7. *Persistent performance*

On average, we find no evidence of a significant positive effect of past performance on future performance for Colombian investment funds. Our empirical evidence is consistent with previous research for non-U.S. funds. Ferreira et al. (2012) found evidence of persistence for U.S. funds and no evidence of past performance in non-U.S. funds; Dahlquist et al. (2000) found no performance persistence for a sample of Swedish funds; Otten and Bams (2002) found performance persistence only for U.K. funds. Although the positive relationship for Colombian investment funds is not significant, these results suggest that a one-standard deviation increase in past performance is related to a subsequent performance increase of 6.7 basis points per month (for the benchmark Sharpe regression model). Comparing our results with those obtained for U.S. funds, such as in Ferreira et al. (2012); Gil-Bazo et al. (2009); Carhart (1997); Brown and Goetzmann (1995); Grinblatt and Titman (1994); and Hendricks, Patel, and Zeckhauser (1993), evidence exists of past performance persistence.

However, Table 27, which contains the re-estimated Equation (23) to group the results based on our empirical style classification, shows significant evidence of positive effects of past performance on future performance for money market funds (cluster 2) for the prospectus benchmark and selection return regression models. However, we also find a nonsignificant negative effect of past performance on future performance for clusters 1, 3, 4, and 5 for all regression models. Our findings extend the evidence for the persistence of the past performance of money market funds, which is consistent with previous research.

9.2.8. *Trading activity (turnover) and performance*

We use turnover as the measure of trading activity, which was defined in chapter 3. As posited by Dahlquist et al. (2008), turnover allows us to capture portfolios' active management. In a well-developed financial market, fund performance might have some advantages over less developed financial markets because of liquidity—higher liquidity results in lower transaction costs (Ferreira et al., 2012). Keim and Madhavan (1997) stated that active investment funds involve higher trading costs, and trading costs are related to fund size (Ferreira et al., 2012; Gil-Bazo et al., 2009). As posited by Ferreira et al. (2012), when an investment fund becomes larger, trading necessarily increases. Some authors found that trading active (turnover) has a positive impact on fund performance (Ferreira et al., 2012; Khorana et al., 2005). On average, we find evidence of a negative relationship between trading activity and fund performance. In Table 26, the turnover coefficient is statistically significant for the first and third regression models; thus, an increase in turnover of one standard deviation is related to a performance decrease of 1.5 basis points per month. Our finding indicates that the liquidity of the Colombian financial market has some disadvantages over that of more developed financial markets. In more developed financial markets, liquidity is higher than in small markets such as ours; thus, the lower performance results from the higher transaction costs that arise from this lower liquidity.

These findings are also consistent in Table 27, which contains the re-estimated Equation (23) to group the results based on our empirical style classification. Evidence of a negative relationship between trading activity and fund performance is consistent with most investment objectives (clusters), although this negative relationship is significant for cluster 2 (money market funds) for the benchmark Sharpe and selection return regression models.

9.2.9. Manager characteristics and performance

Regarding manager structure and performance, ample evidence from U.S. mutual funds exists that shows that funds managed by teams (or more than one manager) exhibit significantly worse performance than funds managed by one manager (Ferreira et al., 2012; Massa, Reuter and Zitzewitz, 2010; Chen et al., 2004; Stein, 2002; Aghion and Tirole, 1997). This phenomenon is explained as follows: when more than one manager manages a fund, there is stronger competition among them because of the additional effort to convince other managers to implement their ideas (Chen et al., 2004). However, evidence also exists that funds managed by a team perform no differently from funds managed by a single manager (Bliss, Potter, and Schwarz, 2008). We find no statistically significant evidence that funds managed by teams perform worse than funds managed by a single person. Conversely, we find a nonsignificant positive relationship between funds managed by a team and performance. Our findings support the argument that funds managed by a team might perform better or no differently from funds managed by a single manager because funds managed by a team might have more resources and connections that can help boost performance. Thus, funds managed by a team might perform better than funds managed by an individual manager. These results are also consistent with Table 27, which contains the re-estimation of Equation (23) to group the results based on our empirical style classification.

Golec (1996) found evidence of a positive relationship between a manager's education and tenure and the performance of U.S. mutual funds because a long tenure may imply greater job security and, hence, less short-term behavior by the manager. A long tenure may imply that the management company finds the manager's performance ability satisfactory, but may also indicate that the manager has fewer better opportunities because of specialized skills or an unspectacular performance record (Golec, 1996). Moreover, Golec (1996) and Chevalier and Ellison (1999) found that years of education, particularly holding an MBA, has a positive relationship with performance because a specialized business education should lead to better performance, and better investment decisions are associated with higher education and stronger managerial skills. On average, we found (Table 26) no statistically significant evidence that tenure is associated with better performance. However, when observing in Table 27 the results grouped by investment objectives, we find strong evidence that tenure is associated with better performance for money market (cluster 2) and income (cluster 5) funds. This positive relationship is consistent for the benchmark Sharpe and selection return models. We also find significant evidence that tenure is not associated with better performance of debt funds (cluster 3). For the other clusters, we find nonsignificant evidence that tenure is associated with performance.

On average, we also find a positive relationship between manager master education and performance, and this relationship is significant at the 5% level for the selection return and benchmark prospectus regression models. However, when the results are grouped by investment objectives, as in Table 27, we find a different result for equity funds (cluster 1) and money market funds (cluster 2). Our results suggest that managers that run an equity or money market fund and have an MBA or postgraduate diploma do not obtain better performance results. Our evidence extends the findings on how managerial characteristics affect performance for non-U.S. funds.

9.3. Interpretation

To summarize our results, in this chapter, we investigated the determinants of investment fund performance in Colombia using a comprehensive data set of open-end and closed-end funds from 2009 to 2015. In our investigation, we encountered common determinants of the performance of investment funds according to previous research but also found some important differences.

Our results extend the findings of investment fund performance determinants for non-U.S. funds, similar to Ferreira et al. (2012) for non-U.S. funds; Dahlquist et al. (2000) for Swedish funds; and Otten and Bams (2002) for U.K. funds.

We find that, on average, fund size is positively related to performance, which is consistent with the findings in Ferreira et al. (2012) for non-U.S. funds. Moreover, we find that investment funds managed by large fund families exhibit worse performance, confirming that when funds reach a certain size, economies of scale are "exhausted," thus eroding performance. This evidence is not consistent with the findings in Ferreira et al. (2012) and some authors for U.S. funds.

We support evidence of a positive relationship between TER and performance as obtained in chapter 6. This evidence agrees with the intuitive expectation that the value that funds create for investors reflects the fees charged because we find that, on average, funds that charge higher fees performance better before expenses but worse after expenses. This result extends the findings in Ferreira et al. (2012) and Gil-Bazo et al. (2009). In addition to the total expense ratio, we find that, on average, investment funds in Colombia with back-end loads are positively related to performance. This condition dissuades redemption and acts in favor of performance because the manager might hold more cash to invest in securities. We find strong evidence of this result for money market funds, which represent more than two-thirds of the funds in our sample. We also find that older equity and older debt funds perform better than younger funds, whereas younger money market funds perform better than older funds. We find evidence that is consistent with previous research that showed that closed-end funds in Colombia are positively related to performance—results that are consistent with previous research (Coles et al., 2000; Khorana et al., 1999). We find evidence that money market funds have a positive effect of past performance on future performance. We also find a nonsignificant effect of past performance on future performance for the rest of the investment objectives (clusters).

Our findings also indicate that the trading activity of Colombian investment funds is negatively related to performance. One explanation for this evidence that is consistent with previous research (Ferreira et al. 2012) is that the liquidity of the Colombian financial market might result in some disadvantages relative to more developed financial markets. In more developed financial markets, the liquidity is higher than in small markets, such as ours. Thus, the lower the liquidity results in higher transaction costs and, hence, lower performance. Our results are also consistent with the smart money hypothesis of Gruber (1996) because we find evidence that the money flows for debt funds, balanced funds, and income funds are positively related to performance. We find no evidence that funds managed by teams perform worse than funds managed by a single person, as is shown in other studies (Ferreira et al., 2012; Massa, Reuter and Zitzewitz, 2010; Chen et al., 2004; Stein, 2002; Aghion and Tirole, 1997). Conversely, we find that funds managed by a team might perform better or no differently than funds managed by a single manager. This evidence extends the findings in Bliss, Potter, and Schwarz (2008) because they also found that funds managed by a team perform no differently from funds managed by a single manager.

Finally, we find no significance difference between the performance of investment funds' determinant's results obtained by our benchmark Sharpe regression model and the benchmark prospectus model. Thus, no conclusive evidence exists that shows that advisory companies in Colombia are interested in intentionally manipulating prospectuses or technical reports to provide a different view of their management activities. However, we realize that all of the information needed to provide a consistent view of investment decisions in the investment fund industry in Colombia is not systematically collected by the regulator or the advisory company, leaving this dispendious task to investors. Therefore, our findings support our hypothesis that investors in Colombia do not have adequate, readily available, and accurate information to evaluate fund performance in the Colombian market.

10. CONCLUSIONS

In this thesis, we provide comprehensive evidence on style classification, fund performance, fee determinants, and the characteristics of Colombian investment funds.

Our unique data set contributes important evidence to the existing finance literature on the performance of investment funds in emerging markets and how incentives, as defined in the advisory contract, affect performance.

We provide evidence of the absence of an industry classification for investment funds in Colombia and that the information provided to investors is too generic. Thus, the local classification provided by either the company advisory or even the regulator has relatively little power in explaining differential fund performance is evident. No conclusive evidence exists to support the argument that advisory companies in Colombia are interested in intentionally manipulating prospectuses or technical reports to present higher alphas, resulting in higher value added over a passive benchmark. However, we realize that all of the information needed to provide a consistent view of investment decisions in the investment fund industry in Colombia is not systematically collected by the regulator or the advisory company, leaving this dispendious task to investors.

We do not suggest that the discussion and examples cited in this thesis represent a complete and comprehensive guide to the proper implementation, understanding, and interpretation of a returns-based style analysis of investment funds in emerging markets. We hope to add our insights to the existent finance literature and believe that this thesis addresses many of the major questions regarding this technique. We believe that we have shown that the techniques employed remain informative and cost-effective analytical tools for investors interested in creating more relevant benchmarks and assessing the asset allocation implications of their mutual fund choices. The method employed provides a consistent view of investment decisions made by managers on behalf of investors. This technique makes investors economize on information flows and exploit comparative advantages. As pointed out in the finance literature, the style analysis procedure described in this document allows such a model to be implemented economically. The style analysis and the empirical style classification can serve as a valuable method to help investors achieve their goals in cost-effective ways.

Our results also contribute to the existing finance literature because they are consistent with previous research. We show that the Sharpe (1992) positive constraints are useful and, as noted by other authors (see por example, Brown et al., 1997; Li and Tiwari; 2009; and Garleanu, Panageas and Yu, 2017), allow the coefficients to be interpreted as vector portfolio weights on investable indices. In addition, the cluster algorithm employed is a complement procedure that is useful when used together to identify common strategies among managers (Brown et al., 1997). The cluster analysis using the algorithm employed by Brown et al. (1997) identifies aggregate behavior, and the Sharpe (1992) procedures help interpret it as a strategy. These findings also contribute to the extant finance literature and show that investment funds in emerging markets can be categorized under this empirical style classification, which is consistent with commonly used asset pricing models. As Brown et al. (1997) noted, the advantage of this method over a heuristic classification is that researchers can use it to decompose styles into more familiar measures, such as time-varying factor loadings and risk premiums.

Therefore, our analysis of investment fund styles provides new evidence on the product offered by company advisors in this market and indicates that the manager's style choices are "colored" by nonperformance considerations—consistent with previous research (Chan et al. 2002). The style dimensions employed are standard practice in the investment fund industry and have been used in prior empirical research. The customized benchmarks computed and the methodology are useful descriptors of fund styles and performance.

Our results are consistence with those obtained in other studies. Investment funds adopt styles that do not deviate markedly from passive benchmarks, with few taking insignificant positions away from the index. This finding might be explained as managers following their self-interests at the expense of the portfolio's performance.

Our findings have important implications for evaluating fund performance, incentives, and risk. In particular, our results on the distribution of fund styles suggest that, overall, investment funds tilt toward money market investing, which might be why, historically, funds on average cannot "beat the market" after costs given that such funds constitute a large (and presumably representative) part of the market.

Accordingly, from the standpoint of an investor, drifts in style with poor part performance introduce variability that deserves monitoring. This finding is consistent with agency theory or behavioral considerations in fund management. According to the finance literature, managers of poorly performing funds may face stronger pressure to attempt something different, follow styles that do not deviate from passive benchmarks, and adopt whichever style has been more successful.

Through this study, we contribute to the understanding of the link between advisory management fees, performance, and how fund characteristics affect compensation fees and performance in the Colombian market.

Our empirical evidence extends the findings in Ferreira et al. (2012) and Gil-Bazo et al. (2009) for non-U.S. funds because we find a positive relationship between fees and performance. Evidence exists that agrees with the intuitive expectation that the value created for investors reflects the fees charged: on average, investments in Colombian funds that charge higher fees have better performance before expenses but worse performance after expenses. Moreover, although we do not find evidence to support the concept that flows are positively related to past performance, we find that a negative performance relative to the benchmark reduces flows, and relatively sophisticated investors in Colombia appear to penalize funds for poor performance. Our results also extend the findings of Gil-Bazo et al. (2009) and Christoffersen and Musto (2002) for non-U.S. funds. Although our findings are for smaller sample funds, we present evidence that the elasticity of demand or performance sensitivity for investment funds in Colombia appears an important determinant of fees because investors that are highly sensitive to net performance are also sensitive to fees.

We realize that other potential alternatives might exist to explain the relationship between performance and fees that we do not explicitly consider in our analysis, such as marketing fees, shareholder statements, and fund governance, among others. Although we believe that the sample used for these investigations is the most comprehensive dataset ever prepared to study investment fund performance in Colombia in terms of both number of funds and number of attributes, our data unfortunately do not allow us to prevent all of these explanations. Thus, we believe that the ability to explain our findings might be limited.

Our investigation revealed the common determinants of investment fund performance according to previous research, but we also found some important differences. Our results extend the findings of investment fund performance determinants for non-U.S. funds, similar to Ferreira et al. (2012) for non-U.S. funds; Dahlquist et al. (2000) for Swedish funds; and Otten and Bams (2002) for U.K. funds. We find that, on average, fund size is positively related to performance, which is consistent with the findings in Ferreira et al. (2012) for non-U.S. funds. Moreover, we find that investment funds managed by large fund families show worse performance, confirming that when funds reach a certain size, economies of scale are "exhausted," and performance is eroded. This evidence is inconsistent with the findings in Ferreira et al. (2012) and some authors for U.S. funds. The trading activity of Colombian investment funds has a negative impact on performance. Consistent with previous research (Ferreira et al. 2012), one explanation for this evidence is that the liquidity of the Colombian financial market might face disadvantages relative to more developed financial markets. More developed financial markets have higher liquidity than small markets such as ours; thus, our lower liquidity results in higher transaction costs and, hence, lower performance.

This thesis intends to complement the extant emerging markets literature on advisory contracts between investors and investment advisors and provides the first evidence in the country on the performance and compensation structure of the investment fund industry.

From a managerial perspective, our study will provide and recommend to investors seeking opportunities to diversify their portfolios in emerging markets, particularly in Colombia, some guidelines that could be useful for understanding the problems faced by these types of investments and maintaining the alignment of interest without affecting the performance and execution of the contract. This analysis will also help governments and regulators formulate their policies that rule these transactions because the effect of incentives on risk-adjusted performance should have important policy implications from the investor protection viewpoint, as well as managing portfolio and reporting transparency by advisory firms.

We do not observe contracts between an individual and a firm. We observe contracts between investors and advisory companies (the fund itself). Thus, we do not observe contracting within the advisory firm. From the investor's viewpoint, internal contracts may not provide fund managers with correct incentives. Such areas of inquiry represent valuable avenues for future research. In addition, given that our time series in the sample is rather short, a further study might consist of extending our sample period to accommodate nonlinear strategies by allowing factor loadings to change on a month-by-month basis, thus avoiding the style classification problems that Brown and Goetzmann (1997) suggested. This technic should compare the style categories formed in the space of past returns to alternate categorization schemes formed in the space of fixed factor loading.

11. CONCLUSIONES (Spanish Version)

Esta tesis provee evidencia exhaustiva acerca de la clasificación de estilos, el rendimiento de los fondos, los determinantes de las comisiones y las características de los fondos de inversión en Colombia.

Nuestro conjunto de datos único aporta importantes pruebas a la literatura financiera existente con respecto al rendimiento de los fondos de inversión en mercados emergentes y la forma en que los incentivos, tal como se definen en el contrato de inversión, afectan al rendimiento.

Suministramos evidencia de la ausencia que existe en Colombia de una adecuada clasificación de industria de los fondos de inversión y que la información proporcionada a los inversionistas es demasiado genérica. La clasificación local proporcionada por las compañías administradoras de fondos o incluso la suministrada por el regulador tiene una capacidad relativamente reducida para explicar el rendimiento de los fondos de manera diferenciada. No encontramos evidencia concluyente que respalde el argumento de que las compañías administradoras de fondos en Colombia están interesadas en manipular deliberadamente los prospectos o los informes técnicos para presentar alfas más elevados, que represente un mayor valor añadido por parte de estas compañías con respecto a un índice de referencia pasivo. Sin embargo, observamos que el regulador o la compañía administradora de fondos no recopila sistemáticamente toda la información necesaria para ofrecer una visión homogénea de las decisiones de inversión en la industria de la inversión en Colombia, lo que deja esta costosa tarea en manos de los inversionistas.

No sugerimos que el análisis y los ejemplos citados en esta tesis representen una guía completa y exhaustiva para una implementación, comprensión e interpretación apropiadas de un análisis de estilos basado en retornos de los fondos de inversión en mercados emergentes. Sin embargo, si esperamos que nuestros hallazgos contribuyan a la literatura financiera existente y consideramos que esta tesis cubre la mayoría de las inquietudes principales asociadas a la industria de fondos de inversión. Mostramos que las técnicas empleadas en este documento siguen siendo herramientas analíticas informativas que no implican costos adicionales para los inversionistas interesados tanto en crear índices de referencia más relevantes como para la evaluación de las implicaciones en la asignación de activos dentro del portafolio de inversión. Los métodos empleados en esta tesis proporcionan una visión homogénea para la toma de decisiones de inversión adoptadas por los gestores en nombre de los inversionistas. Esta técnica permite que los inversionistas puedan economizar en el uso de la información y aprovechar ventajas comparativas. Tal como se indica en la literatura financiera, el procedimiento del análisis de estilos descrito en este documento permite una implementación de manera económica. El análisis de estilos y la clasificación empírica de estilos provistos en este documento pueden servir como un método valioso para ayudar a los inversionistas a alcanzar sus objetivos con los menores costos posibles.

Nuestros resultados también contribuyen a la literatura financiera existente debido a que son consistentes con investigaciones previas. Mostramos que las restricciones positivas en las regresiones de Sharpe (1992) son de amplia utilidad y que, tal como lo señalan otros estudios (ver Brown et al., 1997; Li y

Tiwari, 2009; y Garleanu, Panageas y Yu, 2017), permiten que los coeficientes se interpreten como vectores de ponderaciones dentro del portafolio de inversiones asociados a índices invertibles. Además, el algoritmo de “cluster” o conglomerado empleado es un procedimiento complementario útil cuando se emplea conjuntamente para identificar estrategias comunes entre gestores o gerentes del portafolio (Brown et al., 1997). El análisis de “cluster” que utiliza el algoritmo empleado por Brown et al. (1997) identifica comportamientos similares, y el procedimientos basado en las restricciones de Sharpe (1992) ayudan a interpretarlo como una estrategia. Estos hallazgos también contribuyen a la literatura financiera existente y muestran que los fondos de inversión en los mercados emergentes pueden categorizarse bajo esta clasificación empírica de estilos, la cual está acorde con los métodos de valoración de activos de portafolios utilizados habitualmente. Tal como señalan Brown et al. (1997), la ventaja de este método con respecto a la clasificación heurística es que los investigadores pueden utilizarlo para descomponer los estilos en patrones familiares, tales como los coeficientes condicionales y las primas de riesgo.

Por tanto, nuestro análisis de estilos para los fondos de inversión proporciona nuevas evidencias con respecto al tipo de fondo o producto ofrecido por las compañías administradoras de fondos en este mercado e indican que el estilo del gestor está resaltado por consideraciones de bajo o nulo rendimiento, lo cual es consistente con investigaciones previas en otros mercados (Chan et al. 2002). Las dimensiones de estilo empleadas en este documento son una práctica estándar en la industria de fondos de inversión y se han utilizado en investigaciones empíricas previas. Los índices de referencia calculados y la metodología empleada son descriptores útiles para definir los estilos del fondo y determinar el rendimiento de éstos.

Nuestros resultados son consistentes con los obtenidos en otros estudios previos, pues los resultados indican que los fondos de inversión adoptan estilos que no se desvían sustancialmente de los índices de referencia pasivos, y unos pocos asumen posiciones insignificantes alejadas del índice. Este hallazgo puede explicarse por el hecho de que los gestores siguen su propio interés a expensas del rendimiento del portafolio.

Nuestros hallazgos tienen importantes implicaciones en la evaluación del rendimiento de los fondos, los incentivos y el riesgo. Concretamente, nuestros resultados con respecto a la distribución de estilos de los fondos indican que, en promedio, los fondos de inversión se inclinan hacia inversiones de corto plazo o *money markets*, lo que quizá explique por qué, históricamente y de media, los fondos no pueden "ganarle al mercado" después de costos, dado que tales fondos constituyen una porción significativa (y presumiblemente representativa) del mercado.

En consecuencia, desde el punto de vista de un inversionista, los cambios de estilo en un fondo con rendimiento histórico pobre introducen una variabilidad que merece ser monitoreada. Este hallazgo es consistente con la teoría de agencia o las consideraciones conductuales en la administración de fondos. De acuerdo con la literatura financiera, los gerentes de portafolios con baja rentabilidad pueden enfrentarse a una presión mayor para intentar probar estrategias diferentes, seguir estilos de fondos que no se desvíen de los índices de referencia pasivos y adoptar cualquier estilo que haya sido más exitoso.

A través de este estudio, contribuimos a dar un mayor entendimiento de la relación entre las comisiones de gestión, el rendimiento y cómo las características de los fondos afectan estas comisiones de compensación y el rendimiento en el mercado colombiano.

Nuestras evidencias empíricas amplían los hallazgos obtenidos por Ferreira et al. (2012) y Gil-Bazo et al. (2009) para los fondos fuera de USA, pues observamos que los fondos en Colombia tienen una relación positiva entre las comisiones y el rendimiento. Igualmente, encontramos evidencia que concuerdan con la expectativa intuitiva de que el valor creado para los inversionistas refleja las comisiones cobradas: de media, las inversiones en los fondos colombianos que cobran comisiones más elevadas tienen un mejor rendimiento antes de gastos, pero un peor rendimiento después de éstos. Es más, aunque no encontramos evidencia que respalda el concepto de que los flujos están relacionados positivamente con el rendimiento histórico, observamos que un rendimiento negativo con respecto al índice de referencia reduce los flujos del fondo, y los inversionistas relativamente sofisticados en Colombia parecen penalizar a los fondos con un rendimiento pobre. Nuestros resultados también extienden los hallazgos de Gil-Bazo et al. (2009), y Christoffersen y Musto (2002) para los fondos fuera de USA. Aunque nuestros hallazgos se refieren a una muestra de fondos más pequeñas, presentamos evidencia que la elasticidad de la demanda o la sensibilidad al rendimiento para los fondos de inversión en Colombia parece un determinante importante de las comisiones, dado que los inversionistas que son muy sensibles al rendimiento neto también son sensibles a las comisiones.

Somos conscientes de que existen otras posibles alternativas que no consideramos explícitamente en nuestro análisis, tales como los costos de marketing, declaraciones de accionistas y gobierno corporativo de los fondos, entre otras, que puedan explicar la relación entre el rendimiento y las comisiones. Aunque creemos que la muestra empleada para esta investigación ha sido el conjunto de datos más exhaustivo que jamás se haya recopilado en Colombia para estudiar el rendimiento de los fondos de inversión en el país, tanto en términos de número de fondos como de atributos, nuestros datos lamentablemente no nos permiten prever todas esas explicaciones. Por ello creemos que la capacidad de explicar nuestros hallazgos puede ser limitada.

Nuestra investigación revela determinantes comunes del rendimiento de los fondos de inversión conformes a investigaciones previas, pero también hemos detectado algunas diferencias considerables. Nuestros resultados amplían los hallazgos de la investigación acerca de los determinantes del rendimiento de los fondos de inversión en el caso de fondos no estadounidenses, tal como Ferreira et al. (2012) lo hace para fondos fuera de USA; Dahlquist et al. (2000) para fondos suecos; y Otten y Bams (2002) para fondos británicos. Comprobamos que, en promedio, el tamaño de los fondos está relacionado positivamente con el rendimiento, lo que es acorde con los hallazgos de Ferreira et al. (2012) para fondos no estadounidenses. Además, observamos que los fondos de inversión gestionados por grandes familias de fondos muestran un rendimiento peor, lo que confirma que, al alcanzar un cierto tamaño, las economías de escala se “agotan”, lo que deteriora el rendimiento. Esta evidencia difiere de los hallazgos de Ferreira et al. (2012) y de algunos autores que han estudiado los fondos estadounidenses. El “trading activity” de los fondos de inversión colombianos tiene un efecto negativo en el rendimiento. Consistente con investigaciones previas (Ferreira et al. 2012), una explicación a esta situación es que la liquidez del mercado financiero colombiano puede redundar en algunas desventajas con respecto a mercados financieros más desarrollados. Los mercados financieros más desarrollados tienen una mayor liquidez que los mercados pequeños, como es el caso de Colombia; así, una menor liquidez redunda en mayores costos de transacciones y, por tanto, en un menor rendimiento.

Esta tesis pretende complementar la literatura existente de los mercados emergentes con respecto a los contratos de inversión entre inversionistas y compañías administradoras de fondos, y ofrece las primeras evidencias determinadas de una manera sistemática y empírica en el país con respecto al rendimiento y la estructura de compensaciones de la industria de los fondos de inversión en Colombia.

Desde una perspectiva práctica, este estudio recomienda y sugiere a los inversionistas que busquen oportunidades de diversificar sus portafolios en mercados emergentes, especialmente en Colombia, directrices que pueden ser de utilidad para entender los problemas planteados por este tipo de inversión, así como mantener la alineación de los intereses sin afectar al rendimiento y la ejecución del contrato. Este análisis también ayudará a los gobiernos y a los reguladores a formular las políticas que controlen estas transacciones dado que el efecto de los incentivos en el rendimiento ajustado al riesgo debería tener implicaciones importantes en el diseño de políticas desde el punto de vista de la protección al inversionista, así como de la gestión del portafolio y transparencia en el reporte de la información por parte de las compañías administradoras de fondos de inversión.

Nuestro estudio no se basó en los contratos entre el gerente y la empresa. Nuestro estudio se basó entre los contratos entre el inversionista y la compañía administradora de fondos (el fondo mismo). Así, no nos basamos en la relación contractual dentro de la misma firma administradora de fondos. Desde el punto de vista del inversionista, los contratos internos pueden no ofrecer los incentivos adecuados a los gerentes del portafolio. Tales áreas de análisis pueden ofrecer interesantes vías de investigación futuras. Además, dado que nuestra serie temporal en la muestra es relativamente corta, un estudio posterior podría ampliar el periodo de nuestra muestra para acomodar estrategias no lineales al permitir que los coeficientes cambien de forma mensual, lo que podría evitar los problemas de clasificación de estilos que indicaban Brown y Goetzmann (1997). Esta técnica debería comparar las categorías de estilo formadas con los retornos históricos para alternar los esquemas de categorización formados con los coeficientes fijos.

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APPENDICES

Appendix 1. Sample of two fund´s technical reports issued by their advisory company in Colombia.

Fiduciaria Bogotá

FICHA TÉCNICA
CCAPP FIDUACCIÓN

FIDUCIARIA BOGOTÁ S.A.
septiembre 30 de 2014

VIGILADO SUPERINTENDENCIA FINANCIERA DE COLOMBIA

4. Características de la cartera

4.1.Fecha de Inicio de Operaciones:		29/09/2004
4.2.Valor cartera colectiva (Mill COP):	$	4,229.93
4.3.Valor Unidad:	$	26,473.47
4.4. Numero de Unidades en circulación:		159,779.88
4.5.Numero de Suscriptores:		159
4.6.Tipo de cartera:	Cartera Colectiva Abierta con Pacto de Permanencia	
4.7. Inversión inicial mínima (COP):	$	50,000.00
4.8. Inversión adicional mínima (COP):	No Aplica	
4.9. Retiro mínimo (COP):	No Aplica	
4.10. Saldo mínimo (COP):	$	50,000.00
4.11. Tiempo de preaviso para retiro (Días):	1 día	
4.12. REMUNERACIÓN DE LA SOCIEDAD ADMINISTRADORA: 4.12.1. Remuneración de administración:	3.00%	
4.12.2. Remuneración de éxito	No Aplica	
4.12.3. Remuneración de entrada	No Aplica	
4.12.4. Remuneración de salida	No Aplica	
4.12.5. Remuneración efectivamente cobrada:	2.97%	
4.13. Sanción por retiro anticipado:	Periodo: 30 días	Sanción: P=VR(0.2+(D/E*0.2))/100; P: Penalización; VR: Valor del retiro incluyendo el gravamen a los movimientos financieros si es del caso. D: Días que faltan al vencimiento del encargo con base 365. E: Días a los que se constituyó el encargo.
4.14. Gastos totales de la cartera	6.57%	

5. Calificación de la cartera colectiva

5.1. Calificación	No Aplica
5.2. Fecha de la última calificación	No Aplica
5.3. Entidad calificadora	No Aplica

6. Política de inversión y estrategia

POLÍTICA DE INVERSIÓN CARTERA COLECTIVA ABIERTA CON PACTO DE PERMANENCIA FIDUACCIÓN

Título		Emisor Mínimo	Emisor Máximo	Duración del Portafolio	Calificación Mínima
Inscripción	RNVE	0%	100%	El Plazo promedio ponderado de los instrumentos de renta fija será máximo de 365 días.	Todas las inversiones de renta fija deben tener calificación mínima de dos (2) para el corto plazo.
	Bolsa de valores	0%	100%		
Clase inversión	Renta fija (1)	0%	40%		
	Renta variable	60%	100%		
Moneda	Pesos colombianos	0%	100%		
Clase	Acciones (2)	60%	100%		
	Cuentas de Ahorro y Corriente	0%	40%		
	Participaciones en carteras colectivas	0%	40%		
Operaciones de Liquidez(3)	Repos y Simultaneas Activas	0%	30%	Plazo máximo de operaciones Repo y Simultaneas será de 90 días	
	Repos y Simultaneas Pasivas	0%	30%		
	Transferencia temporal de valores	0%	30%		

(1) Concentración por emisor hasta 10% de los activos totales de la cartera.

(2) Solo se invertirá en acciones inscritas en la Bolsa de Valores, que estén establecidas en Colombia. Concentración por emisor hasta 40% de los activos totales de la cartera.

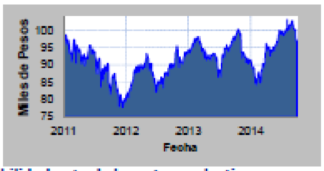
(3) La realización de las operaciones de repo simultaneas y de transferencia temporal de valores sean activas o pasivas, en su conjunto no podrán representar más del 30% del los activos de la cartera colectiva.

Nota: Los porcentajes aquí señalados se calcularán con base en los activos de la cartera colectiva.

Conforme a lo establecido en el Artículo 3.1.9.1.2 del Decreto 2555 de 2010, Fiduciaria Bogotá S.A. ha contratado como administrador a BTG Pactual-Comisionista de Bolsa, para que en su nombre y por su cuenta administre el portafolio de la Cartera Colectiva Abierta con Pacto de Permanencia Fiduacción, conforme a los términos establecidos en el contrato de administración suscrito entre las partes y el manual operativo, situación que no exime a Fiduciaria Bogotá S.A. de su responsabilidad como administrador profesional y de las actuaciones adelantadas por el mandatario.

7. Evolución del valor de la cartera colectiva

7.1. Evolución de 100.000 COP invertidos hace 3 años:



7.2. Evolución valor de la unidad en los últimos 3 años:

8. Rentabilidad neta de la cartera colectiva

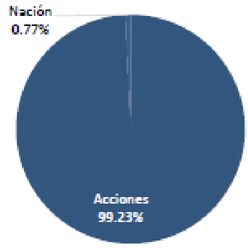
	Últimos			Anual			
	30 días	180 días	365 días	Año Corrido	2013	2012	2011
8.1. Rentabilidad Efectiva	-51.616%	0.527%	-0.608%	8.036%	-3.188%	18.301%	-20.543%
8.2. Volatilidad de la Rentabilidad	23.792%	16.919%	6.739%	24.236%	11.967%	63.477%	11.048%

9. Información de plazos y duración

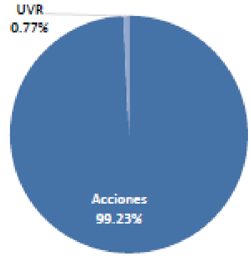
9.1. Detalle de Plazos	Participación
1-180 DIAS	99.229%
181-360 DIAS	0.000%
361-1095 (1 A 3 AÑOS)	0.771%
1096-1825 (3 A 5 AÑOS)	0.000%
MAS DE 1825 (MAS DE 5 AÑOS)	0.000%
Total	100%

9.2. Plazo Promedio de las inversiones	
Días	Años
4.295	0.012

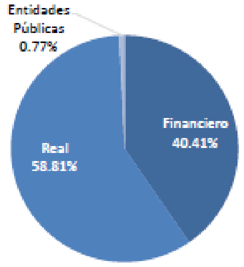
10.1. Composición portafolio por calificación



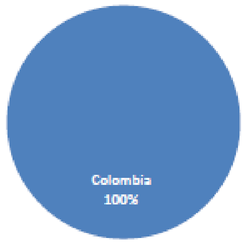
10.2. Composición portafolio por tipo de renta



10.3. Composición portafolio por sector económico



10.4. Composición portafolio por país emisor



11. Composición del activo de la cartera colectiva

12. Principales inversiones de la cartera colectiva

	Emisor	Participación frente al total de la Inversión (%)
1	SURAMERICANA DE INVERSIONES	13.59%
2	ECOPETROL SA	13.04%
3	BANCOLOMBIA S.A	11.02%
4	GRUPO ARGOS SA	8.89%
5	BANCO DAVIVIENDA S A	7.30%
6	GRUPO NUTRESA S.A.	6.63%
7	CEMENTOS ARGOS S A	5.86%
5	CEMEX LATAM HOLDINGS S.A.	4.26%
9	GRUPO AVAL ACCIONES Y VALORES S A	4.13%
10	ISAGEN S.A ESP	4.03%
Total		78.74%

13. Empresas vinculadas y relacionadas con la Administradora

Fidubogotá S.A. es una Sociedad Fiduciaria filial Banco de Bogotá, entidad perteneciente al Grupo Aval.

15. Información de contacto del revisor fiscal y contralor normativo

Nombre Revisor Fiscal: KPMG Ltda. **Teléfono:** Bogotá 6188000
Dirección Electrónica: lcastano@kpmg.com
El Revisor Fiscal es el mismo de la Administradora: Si X No___

Nombre Contralor: Maria Luisa Peña **Teléfono:** Bogotá 57-1-3215030
Dirección Electrónica: mpena@mlpabogados.com

14. Hoja de vida del administrador de la cartera colectiva

Nombre: Jaime Andrés Martínez Henao
Profesión: Economista – Universidad del Valle
Estudios Especializados: Postgraduate Certificate in Finance, Trading and Analysis - London School of Business and Finance. Maestría en Administración Financiera y Especialización en Finanzas - Universidad EAFIT
Experiencia: FIDUCIARIA BOGOTÁ-Gerente de Portafolios de Inversión (2012); FIDUCIARIA BOGOTÁ-Trader Senior Carteras Colectivas (2007-2011); FIDUCOMERCIO-Trader (2005-2007); ALIANZA FIDUCIARIA-Trader (2004-2005); ALIANZA FIDUCIARIA-Asistente de la Vicepresidencia Financiera (2003-2004)
Otras carteras a su cargo: ÓPTIMO - SUMAR - FIDUGOB - CUBRIR

16. Información del Contacto del Defensor del Consumidor Financiero

Nombre: Octavio Gutierrez Díaz **Teléfono:** Bogotá 332 00 32 Extensión: 3397, 3398
Dirección Electrónica: defensoriaconsumidorfinanciero@bancodebogota.com.co

Este material es para información de los inversionistas y no está concebido como una oferta o una solicitud para vender o comprar activos. La información contenida es sólo una guía general y no debe ser usada como base para la toma de decisiones de inversión. En relación con la cartera colectiva existe un prospecto de inversión y un contrato de suscripción de derechos, donde se contiene una información relevante para su consulta y podrá ser examinada en www.fidubogota.com. Las obligaciones asumidas por la Fiduciaria Bogotá S.A., de la Cartera Colectiva Abierta Sumar relacionadas con la gestión del portafolio, son de medio y no de resultado. Los dineros entregados por los suscriptores a la cartera colectiva no son un depósito, ni generan para la sociedad administradora las obligaciones propias de una institución de depósito y no están amparadas por el seguro de depósito del Fondo de Garantías de Instituciones Financieras FOGAFIN, ni por ninguno de dicha naturaleza. La inversión en la cartera colectiva está sujeta a los riesgos derivados de los activos que componen el portafolio de la respectiva cartera colectiva. Los datos suministrados reflejan el comportamiento histórico de la cartera colectiva, pero no implica que su comportamiento en el futuro sea igual o semejante.

Fiduciaria Corficolombiana

Cartera Colectiva Abierta Valor Plus Compartimento IV

Datos con corte al 30 de septiembre de 2014

Calificado por Fitch Ratings Colombia

AAA en riesgo crediticio, 2 en riesgo de mercado

Características de la cartera colectiva

Fecha de inicio de operaciones	02/11/2012
Valor cartera colectiva (Millones Cop)	71.053
Valor unidad	10.784,93
Número de unidades en circulación	6.588.203
Número de suscriptores	8
Número de encargos	8
Tipo de cartera colectiva	Cartera Colectiva Abierta
Inversión inicial Mínima	8.000.000.000
Inversión adicional Mínima	1
Retiro mínimo	N/A
Saldo Mínimo	8.000.000.000
Tiempo de preaviso por retiro (Días)	1

Sanción por retiro anticipado	Periodo	Condiciones para cobro
	No. Días	N/A

Remuneración y gastos de la sociedad administradora

Remuneración de la administración	0,85% E.A.

Remuneración de éxito	Porcentaje	Condiciones para su cobro
	N/A	N/A

Remuneración de entrada	N/A
Remuneración de salida	N/A
Remuneración efectivamente cobrada	0,85% E.A.
Gastos totales de la cartera (incluye la remuneración)	0,95% E.A.

Calificación de la cartera colectiva

Riesgo de mercado	Riesgo de crédito
2	AAA
Fecha de la última calificación de la cartera	Entidad calificadora
26/11/2013	Fitch Ratings Colombia

Política de inversión

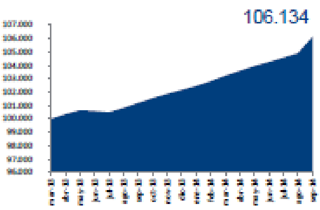
Objetivo de la inversión:
Cartera colectiva destinada a realizar inversiones en títulos de deuda de alta liquidez y baja duración, logrando una fuerte estructura de caja que le permita atender la volatilidad de los recursos administrados.

Política general de inversión:
La sociedad administradora invierte los recursos del compartimento en activos de renta fija inscritos o no en el RNVE. Se podrán realizar operaciones de reporto, simultáneas y transferencia temporal de valores, tanto activas como pasivas, sin exceder el 30% de los activos de la cartera. Adicionalmente, se podrán mantener hasta el 50% del valor de los recursos administrados en depósitos en cuentas corrientes y/o de ahorros.

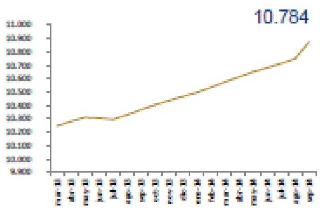
Perfil de riesgo del inversionista:
Se considera que el perfil general de riesgo de la cartera colectiva es conservador, por cuanto la política de inversión es en valores de alta calidad crediticia, con un sistema de administración de riesgo de mercado adecuado, un modelo interno que permite prever necesidades de liquidez y una política de diversificación clara.

Evolución del valor de la cartera colectiva

Evolución de 100.000 Cop invertidos hace 3 años (en pesos)



Evolución valor de la unidad en los últimos 3 años (en pesos)



Rentabilidad neta de la cartera colectiva

	Últimos			Año Corrido	Anual		
	30 días	180 días	365 días		2013	2012	2011
Rentabilidad efectiva	4,27%	4,00%	4,02%	4,07%	3,84%	-	
Volatilidad de la rentabilidad	0,17%	0,06%	0,32%	0,25%	0,97%		-
Var*							

* Información en blanco hasta tanto la Superintendencia Financiera expida instrucciones sobre el particular.

Información de plazos y maduración

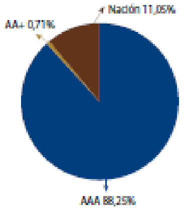
Detalle maduración	Participación %	Maduración promedio del portafolio: Días	Años	Maduración promedio del Total de Activos: Días	Años
1 a 180 días	28,17%	329,67	0,903	218,17	0,598
181 a 360 días	32,82%				
1 a 3 años	39,00%				
3 a 5 años					
Más de 5 años					
	100,00%				

Las obligaciones asumidas por la Fiduciaria Corficolombiana S.A., de la Cartera Colectiva Abierta Valor Plus Compartimento IV relacionadas con la gestión del portafolio, son de medio y no de resultado. Los dineros entregados por los suscriptores a la cartera colectiva no son un depósito, ni generan para la sociedad administradora las obligaciones propias de una institución de depósito y no están amparados por el seguro de depósito del Fondo de Garantías de Instituciones Financieras FOGAFÍN, ni por ninguno de dicha naturaleza. La inversión en la cartera colectiva está sujeta a los riesgos derivados de los activos que componen el portafolio. Los datos suministrados reflejan el comportamiento histórico de la cartera colectiva, pero no implica que su comportamiento en el futuro sea igual o semejante.

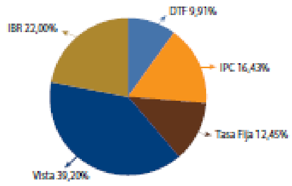
Composición del portafolio

Datos con corte al 30 de septiembre de 2014

Por calificación

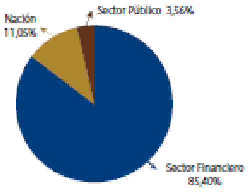


Por tipo de renta

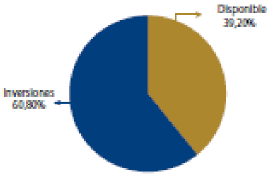


Por país emisor

Por sector económico



Composición del activo de la cartera



Principales inversiones de la cartera colectiva

	Emisor	Participación frente al total de inversión %
1	Corficolombiana	15,71%
2	Banco de Occidente	14,56%
3	Banco de Bogotá	14,01%
4	La Nación	11,05%
5	Banco Colpatria	8,52%
6	Bancolombia S.A.	5,99%
7	Banco Davivienda	5,41%
8	Leasing Bancolombia	5,00%
9	Banco AV Villas	4,40%
10	Findeter	3,65%
	Total	88,20%

Información de contacto del revisor fiscal de la cartera colectiva

Nombre: Hugo Alonso Magaña Salazar
Teléfono: (1) 618 80 00
Dirección electrónica: hmagana@kpmg.com.co
El revisor fiscal es el mismo de la administradora: SI ☒ No ☐

Empresas vinculadas y relacionadas con la sociedad administradora

Matriz: Corporación Financiera Colombiana
Filiales: Fiduciaria Corficolombiana/Leasing Corficolombiana

Información de contacto del contralor normativo

Nombre: Jose Federico Ustáriz González
E-mail: ejustariz@etb.net.co
Teléfono: (1) 642 12 38/9

Hoja de vida del administrador de la cartera colectiva

Nombre: Juan Ricardo Saavedra Silva
Profesión: Economista y Negociador Internacional
Estudios Especializados: Maestría en Finanzas
Experiencia: 5 años en el Sector Financiero
E-mail: juan.saavedra@fiduciariacorficolombiana.com
Otras carteras a su cargo: Capital Plus, Renta Plus, Confianza Plus y Multiplicar.

Información de contacto del defensor del consumidor financiero

Defensor Principal: Darío Laguado Monsalve
Dirección: Calle 70 A No. 11 - 83 Bogotá
Teléfono: (1) 543 98 50/ 235 16 04/ 249 25 97
E-mail: dario@defensorialaguadogiraldo.com.co | defensorialg@yahoo.com

Fiduciaria Corficolombiana S.A. Sociedad Fiduciaria

Appendix 2. Variables Definition:

Variables	Database	Data item used	Explanation	Frequency
Contract Variables				
Effective fee rate	Monthly report/Legal Prospectus	effective_fee_rate	Effective marginal compensation rate based on the current reported information by each fund	Monthly
Cole´s incentive rate	Monthly report/Legal Prospectus	coles_rate	Difference between the last and the first fee rates divided by the effective fee rate. Massa and Patgiri (2009)	Monthly
Weighted incentive rate	Monthly report/Legal Prospectus	weighted_rate	Weighted average of the fee rates divided by the first applicable fee rate. Massa and Patgiri (2009)	Monthly
Incentive ratio	Monthly report/Legal Prospectus	incentive_ratio	Ratio of the fee rates that would be applicable due to a 10% increase in TA versus a 10% decrease in TA of the fund. Massa and Patgiri (2009)	Monthly
Concave_Linear dummy	Monthly report/Legal Prospectus	concave_linear_d	A dummy variable that takes the value of 1 for funds with concave fee schedule and 0 for funds with a linear fee schedule	Monthly
Performance based fee	Monthly report/Legal Prospectus	performance_d	A dummy variable that indicates the value of 1 if the fund has an own-performance-based fee in the contract and 0 otherwise	Monthly
Front Load Fees	Monthly report/Legal Prospectus	frontl_d	A dummy variable that indicates the value of 1 if the fund has a front loads fee in the contract and 0 otherwise	Monthly
Back Load Fees	Monthly report/Legal Prospectus	backl_d	A dummy variable that indicates the value of 1 if the fund has a back loads fee in the contract and 0 otherwise	Monthly
Fund Variables				
Fund performance	Colombian´s SEC	daily_return	Daily fund return	Daily
	Colombian´s SEC	monthly_return	Monthly fund return: {(Amount unit t/Amount unit t-1)-1}	Monthly
Fund TA	Colombian´s SEC	fund_TA	Total Assets of the Fund in COP$ Million	Monthly - Daily
Advisory Age	Colombian´s SEC/Monthly Report	adv_age	Number of months since the Advisory fund launch date	Monthly
Fund Age	Colombian´s SEC/Monthly Report	fund_age	Number of months since the fund launch date (Lipper).	Monthly
Fund Return Volatility	Colombian´s SEC	fund_volatility_30d	Standard deviation of returns of the fund during the 30 days of the reported date of Super Financiera information	Monthly
	Colombian´s SEC	fund_volatility_12m	Standard deviation of returns of the fund in the 12 months prior to the reported date	Monthly
Net Money Inflow COP$ (estimated)	Colombian´s SEC	fund_flow_std	Net inflow (in COP$ Million) into the fund in a month. This is difference between= fund_TA t - fund_TA t-1 - return_size	Monthly
New Money Inflow % (estimated)	Colombian´s SEC	fund_flow_new	Net inflow into the fund as a percentage of TA. This variable captures the proportion between fund flow and Fund_TA = (Fund_TA in t - Fund_TA in t-1 - Return_Size) / Fund_TA in t-1	Monthly
Money inflow In (estimated)	Colombian´s SEC	fund_flow_in	This variable (in COP$ Million) is determined as the sum of positive differences during a month among fund_size in a dailly basis: fund_TA day t - fund_TA day t-1	Monthly
Money inflow Out (estimated)	Colombian´s SEC	fund_flow_out	This variable (in COP$ Million) is determined as the sum of negative differences during a month among fund_size in a dailly basis: fund_TA day t - fund_TA day t-1	Monthly
Turnover (estimated)	Colombian´s SEC	turnover	Turnover is defined as the minimum of sales or purchases divided by total assets of the fund (Dahlquist et al, 2000; Massa et al, 2009; Ferreira et al, 2012). Considering that this variable has not been considered by the regulator in Colombia, we intended to estimate the sales or purchases based on the daily total asset in local currency of fund i. If we took the difference between the total asset in local currency of fund i in t+1 and total asset in local currency of fund i in t-1, and then we subtract the assuming returns of fund i in local currency, we can make an estimation of the purchases and sales daily. A positive difference during the month t in this result will be assumed as flow_in in fund i, that is, a purchasing. A negative difference during the month in this result will be assumed as flow_out in fund i, that is, a sale. This approach is an approximation of the purchases and sales for funds i, however, given the absence of said information whether by the regulator or by the investment fund advisors, we believe that this methodology is a good proxy to estimate turnover, as trading activity measure.	Monthly
Minimum required invesment	Monthly report/Legal Prospectus	min_invest	Lowest minimum initial investment required to become an investor of the fund (in COP$ Million)	Monthly
Average account size	Colombian´s SEC	account_size	Average account Size= fund_size/investors. This is a control variable (in COP$ Million)	Monthly
Total Expense Ratio	Monthly report/Legal Prospectus	TER	Total annual expenses as a fraction of TA reported by each fund. When it is not available the Effective_Fee_Rate is taken	Monthly
Open Closed Fund	Colombian´s SEC	open_closed_d	A dummy variable that indicates the value of 1 if the fund is an open-end fund and 0 if the fund is a closed-end fund	Monthly
Manager Variables				
Sub-Advisory Management Fund	Monthly report/Legal Prospectus	subadv_d	Dummy variable that equals 1 when the fund is managed by a team or a Sub Advisory Company, and 0 when the fund is managed by one person (Lipper).	Monthly
Manager gender	Monthly report/Legal Prospectus	gender	A dummy variable that indicates the value of 1 if the fund´s manager is male and 0 female	Monthly
Tenure Manager	Monthly report/Legal Prospectus	tenure_manager	Years of experience of fund´s manager	Monthly
Manager Postgraduate Certific dummy	Monthly report/Legal Prospectus	manager_adv_d	A dummy variable that equals 1 if the fund´s manager has postgraduate diploma and 0 otherwise	Monthly
Manager Master Education dummy	Monthly report/Legal Prospectus	manager_master_d	A dummy variable that indicates the value of 1 if the fund´s manager has Master or PhD degree and 0 otherwise	Monthly

Appendix 3. Indices definition:

Geog	Class	Type	Index	Description	
Domestic	Debt	Fixed Income Government	COLTES	Includes all references for type B TES securities in pesos with maturities longer than 1 year	The Colombian Securities Exchange (BVC) has developed a series of total return indices weighted by market capitalization on the Colombian Government debt bonds in COP (Colombian pesos), this indices are COLTES Government bond Index, COLTES CP (Short Term) and COLTES LP (Long Term). These indices have been designed to provide investors with market references easy to replicate, which can be used to measure the general evolution of the Colombian Government bonds "B TES securities".
			COLTES CP	Includes all fixed-income COLTES index references that with maturities between 1 and 5 years	
			COLTES LP	Includes all fixed-income COLTES index references with maturities longer than 5 years.	
			COLTES UVR	Includes all references for type B TES securities in UVR (Unidad de Valor Real) with maturities longer than 1 year.	The Colombian Securities Exchange (BVC) has developed a total return index weighted by market capitalization on the Colombian Government debt bonds in UVR (Unidad de Valor Real) called COLTES UVR. This index has been designed to provide investors with a market reference easy to replicate, which can be used to measure the general evolution of the Colombian Government bonds "B TES securities linked to UVR".
		Money Market	COLIBR	The COLIBR is the reference index employed to follow the development of the Colombian Money Market. It replicates an investment that produces the Overnight IBR rate (Inter Bank Rate) that is calculated and published by the Central Bank daily. Due to how the Overnight rate is calculated and the index is replicated, the overnight IBR is only calculated on business days.	
			TCC	TCC is an interest rate composite, calculated as the weighted average of the interest rates on 90 days Certificates of Deposits (CDs) offered by private financial corporation.	
			DTF	DTF is an interest rate composite, calculated as the weighted average of the interest rates on 90- day Certificates of Deposits (CDs) offered by Colombian banks and financial institutions. This index has been used as an important benchmark rate in Colombia.	
		CPI	COCPI	CPI - Inflation Rate Colombia	
		Exchange rate	TRM Index	US Dollar - Colombian Peso	
Foreign		Fixed Income	LEGATRUU	LEGATRUU - The BarCap Global Aggregate TR bond index is a very broad index of all types of fixed income instruments including sovereign, investment grade corporate and high yield across developed and emerging markets.	
Domestic	Equity	Variable Income Colombia	COLEQTY	COLEQTY is a general index composed of the top 40 largest and performing shares on the Colombian Securities Exchange (BVC). The weight of each share is determined by the floating weight (adjusted cap) of each of the constituents.	
			COLSC	COLSC is an index made up by the 15 smallest companies in terms of market capitalization within COLEQTY index (BVC)	
			COLCAP	Colombia COLCAP Index is a market-capitalization weighted index that includes the 20 most liquid stocks listed in the BVC (Bolsa de Valores de Colombia). The market cap of the company represents the weighting on the index. (Bloomberg)	
			COLIR	Colombia COLIR index includes the shares of the companies with the IR Recognition, granted according to BVC Regulations and are constituents of the Colombia COLEQTY index. The weight of each share is determined by the free float adjusted by market cap of each of the constituents. The IR recognition is an instrument developed by BVC to reflect best practices in information release and investor relation.	
Foreign		Variable income	ACWI Index	MSCI ACWI captures large and mid cap representation across 23 Developed Markets (DM) and 23 Emerging Markets (EM) countries*. With 2,484 constituents, the index covers approximately 85% of the global investable equity opportunity set. (Bloomberg)	
Domestic	Real Estate	Real Estate	PEI	Index Real Estate Assets in Colombia (Private Equity Index)	

Appendix 4. Constrained Regression: Stata code used to implement a quadratic programming algorithm, also known as style analysis (Sharpe 1988, 1992).

```
set more off

mat mat_ESTIMADOS_res = J(184,44,.)

global codes 2276	2852	2971	2990	3010	3019	3031	3040	3049	3078
	3644	3685	3721	3781	3794	3814	3832	3848	3895	4527	4786
	5682	5690	8686	8734	8742	9438	9448	9452	9453	9633	9641
	9644	9645	9647	9792	10025	10026	10440	10482	10522	10533	10539
	10542	10556	10579	10587	10647	10648	10649	10650	10651	10653	10654
	10656	10659	10660	10662	10663	10665	10666	10667	10668	10779	10799
	10813	10824	10877	10936	10981	11014	11022	11025	11149	11151	11165
	11169	11170	11171	11174	11176	11286	11356	11403	11407	11424	11427
	11462	11470	11476	11483	11627	11714	11962	12050	13174	13520	13525
	14280	14773	14811	15252	15397	15400	15818	15862	16211	16373	16412
	16736	16863	16866	16912	17101	17402	17403	17653	17658	17660	17661
	17727	18252	18462	18926	19118	19119	19185	19371	19466	20535	20537
	20660	20984	20985	21521	21522	21651	21652	21892	22119	22275	22437
	22444	22448	22817	23108	23347	23487	23676	23721	23999	24299	24300
	25392	25743	25826	26003	26004	26433	27081	27627	28076	28854	29133
	30383	30385	30602	30606	31508	33186	33187	33355	33640	33642	33643
	34166	34908	36570	37238	37240	41248	51954	51959

local i=1
foreach fund_code in $codes {
	{
	display "code_fund: `fund_code' "

sum Wmonthly_return if fund_code==`fund_code'

cap scalar var_mr = r(Var)

local ma1 (1/(1+exp({t2})+exp({t3})+exp({t4})+exp({t5})+exp({t6})+exp({t7})+exp({t8})))
local ma2 (exp({t2})/(1+exp({t2})+exp({t3})+exp({t4})+exp({t5})+exp({t6})+exp({t7})+exp({t8})))
local ma3 (exp({t3})/(1+exp({t2})+exp({t3})+exp({t4})+exp({t5})+exp({t6})+exp({t7})+exp({t8})))
local ma4 (exp({t4})/(1+exp({t2})+exp({t3})+exp({t4})+exp({t5})+exp({t6})+exp({t7})+exp({t8})))
local ma5 (exp({t5})/(1+exp({t2})+exp({t3})+exp({t4})+exp({t5})+exp({t6})+exp({t7})+exp({t8})))
local ma6 (exp({t6})/(1+exp({t2})+exp({t3})+exp({t4})+exp({t5})+exp({t6})+exp({t7})+exp({t8})))
local ma7 (exp({t7})/(1+exp({t2})+exp({t3})+exp({t4})+exp({t5})+exp({t6})+exp({t7})+exp({t8})))
local ma8 (exp({t8})/(1+exp({t2})+exp({t3})+exp({t4})+exp({t5})+exp({t6})+exp({t7})+exp({t8})))

#delimit ;
nl (Wmonthly_return = `ma1'*r_coltes + `ma2'*r_coltesuvr + `ma3'*r_cocpi_index
+ `ma4'*r_legatruu + `ma5'*r_colibr_index + `ma6'*r_colcap_index
+ `ma7'*r_pei_index + `ma8'*r_tcc_rate + {a9}) if fund_code==`fund_code', vce(robust) delta(1e-
7) nolog;
#delimit cr

cap scalar obs = e(N)
cap scalar var_error = e(msr)
cap scalar SSmodel = e(mss)
cap scalar SSresidual = e(rss)
```

```
cap scalar SStotal = e(tss)
cap scalar dftotal = e(df_t)
cap scalar dfresidual = e(df_r)

local na1
1/(1+exp(_b[t2:_cons])+exp(_b[t3:_cons])+exp(_b[t4:_cons])+exp(_b[t5:_cons])+exp(_b[t6:_con
s])+exp(_b[t7:_cons])+exp(_b[t8:_cons]))
local na2
exp(_b[t2:_cons])/(1+exp(_b[t2:_cons])+exp(_b[t3:_cons])+exp(_b[t4:_cons])+exp(_b[t5:_cons])
+exp(_b[t6:_cons])+exp(_b[t7:_cons])+exp(_b[t8:_cons]))
local na3
exp(_b[t3:_cons])/(1+exp(_b[t2:_cons])+exp(_b[t3:_cons])+exp(_b[t4:_cons])+exp(_b[t5:_cons])
+exp(_b[t6:_cons])+exp(_b[t7:_cons])+exp(_b[t8:_cons]))
local na4
exp(_b[t4:_cons])/(1+exp(_b[t2:_cons])+exp(_b[t3:_cons])+exp(_b[t4:_cons])+exp(_b[t5:_cons])
+exp(_b[t6:_cons])+exp(_b[t7:_cons])+exp(_b[t8:_cons]))
local na5
exp(_b[t5:_cons])/(1+exp(_b[t2:_cons])+exp(_b[t3:_cons])+exp(_b[t4:_cons])+exp(_b[t5:_cons])
+exp(_b[t6:_cons])+exp(_b[t7:_cons])+exp(_b[t8:_cons]))
local na6
exp(_b[t6:_cons])/(1+exp(_b[t2:_cons])+exp(_b[t3:_cons])+exp(_b[t4:_cons])+exp(_b[t5:_cons])
+exp(_b[t6:_cons])+exp(_b[t7:_cons])+exp(_b[t8:_cons]))
local na7
exp(_b[t7:_cons])/(1+exp(_b[t2:_cons])+exp(_b[t3:_cons])+exp(_b[t4:_cons])+exp(_b[t5:_cons])
+exp(_b[t6:_cons])+exp(_b[t7:_cons])+exp(_b[t8:_cons]))
local na8
exp(_b[t8:_cons])/(1+exp(_b[t2:_cons])+exp(_b[t3:_cons])+exp(_b[t4:_cons])+exp(_b[t5:_cons])
+exp(_b[t6:_cons])+exp(_b[t7:_cons])+exp(_b[t8:_cons]))
local na9 _b[a9:_cons]

nlcom (a1: `na1') (a2: `na2') (a3: `na3') (a4: `na4') (a5: `na5') (a6: `na6') (a7: `na7') (a8: `na8')
(a9: `na9') , post cformat(%9.4f)
cap scalar sumcoeff= _b[a1]+_b[a2]+_b[a3]+_b[a4]+_b[a5]+_b[a6]+_b[a7]+_b[a8]

        display "Sum of coefficients: " sumcoeff
        display "SSmodel: " SSmodel
        display "SSresidual: " SSresidual
        display "SStotal: " SStotal

        cap scalar beta_0 = _b[a9]
        cap scalar beta_1 = _b[a1]
        cap scalar beta_2 = _b[a2]
        cap scalar beta_3 = _b[a3]
        cap scalar beta_4 = _b[a4]
        cap scalar beta_5 = _b[a5]
        cap scalar beta_6 = _b[a6]
        cap scalar beta_7 = _b[a7]
        cap scalar beta_8 = _b[a8]
        cap scalar R2= SSmodel/SStotal
        cap scalar R2a= 1 - (((1-R2)*(dftotal))/dfresidual)

        display "R2: " R2

        cap scalar se_beta_0 = _se[a9]
        cap scalar se_beta_1 = _se[a1]
        cap scalar se_beta_2 = _se[a2]
        cap scalar se_beta_3 = _se[a3]
```

```
cap scalar se_beta_4 = _se[a4]
cap scalar se_beta_5 = _se[a5]
cap scalar se_beta_6 = _se[a6]
cap scalar se_beta_7 = _se[a7]
cap scalar se_beta_8 = _se[a8]
cap	scalar t_beta_0 = _b[a9] / _se[a9]
cap	scalar t_beta_1 = _b[a1] / _se[a1]
cap	scalar t_beta_2 = _b[a2] / _se[a2]
cap	scalar t_beta_3 = _b[a3] / _se[a3]
cap	scalar t_beta_4 = _b[a4] / _se[a4]
cap	scalar t_beta_5 = _b[a5] / _se[a5]
cap	scalar t_beta_6 = _b[a6] / _se[a6]
cap	scalar t_beta_7 = _b[a7] / _se[a7]
cap	scalar t_beta_8 = _b[a8] / _se[a8]
cap	scalar p_beta_0 = 2*normal(-abs(t_beta_0))
cap scalar p_beta_1 = 2*normal(-abs(t_beta_1))
cap scalar p_beta_2 = 2*normal(-abs(t_beta_2))
cap scalar p_beta_3 = 2*normal(-abs(t_beta_3))
cap scalar p_beta_4 = 2*normal(-abs(t_beta_4))
cap scalar p_beta_5 = 2*normal(-abs(t_beta_5))
cap scalar p_beta_6 = 2*normal(-abs(t_beta_6))
cap scalar p_beta_7 = 2*normal(-abs(t_beta_7))
cap scalar p_beta_8 = 2*normal(-abs(t_beta_8))

cap matrix mat_ESTIMADOS_res[`i',1] == `fund_code'
cap matrix mat_ESTIMADOS_res[`i',2] == beta_0
cap matrix mat_ESTIMADOS_res[`i',3] == beta_1
cap matrix mat_ESTIMADOS_res[`i',4] == beta_2
cap matrix mat_ESTIMADOS_res[`i',5] == beta_3
cap matrix mat_ESTIMADOS_res[`i',6] == beta_4
cap matrix mat_ESTIMADOS_res[`i',7] == beta_5
cap matrix mat_ESTIMADOS_res[`i',8] == beta_6
cap matrix mat_ESTIMADOS_res[`i',9] == beta_7
cap matrix mat_ESTIMADOS_res[`i',10] == beta_8
cap matrix mat_ESTIMADOS_res[`i',11] == R2
cap matrix mat_ESTIMADOS_res[`i',12] == R2a
cap matrix mat_ESTIMADOS_res[`i',13] == obs
cap matrix mat_ESTIMADOS_res[`i',14] == sumcoeff
cap matrix mat_ESTIMADOS_res[`i',15] == SSmodel
cap matrix mat_ESTIMADOS_res[`i',16] == SSresidual
cap matrix mat_ESTIMADOS_res[`i',17] == SStotal

cap matrix mat_ESTIMADOS_res[`i',18] == se_beta_0
cap matrix mat_ESTIMADOS_res[`i',19] == se_beta_1
cap matrix mat_ESTIMADOS_res[`i',20] == se_beta_2
cap matrix mat_ESTIMADOS_res[`i',21] == se_beta_3
cap matrix mat_ESTIMADOS_res[`i',22] == se_beta_4
cap matrix mat_ESTIMADOS_res[`i',23] == se_beta_5
cap matrix mat_ESTIMADOS_res[`i',24] == se_beta_6
cap matrix mat_ESTIMADOS_res[`i',25] == se_beta_7
cap matrix mat_ESTIMADOS_res[`i',26] == se_beta_8
cap matrix mat_ESTIMADOS_res[`i',27] == t_beta_0
cap matrix mat_ESTIMADOS_res[`i',28] == t_beta_1
cap matrix mat_ESTIMADOS_res[`i',29] == t_beta_2
cap matrix mat_ESTIMADOS_res[`i',30] == t_beta_3
cap matrix mat_ESTIMADOS_res[`i',31] == t_beta_4
cap matrix mat_ESTIMADOS_res[`i',32] == t_beta_5
```

```
	cap matrix mat_ESTIMADOS_res[`i',33] == t_beta_6
	cap matrix mat_ESTIMADOS_res[`i',34] == t_beta_7
	cap matrix mat_ESTIMADOS_res[`i',35] == t_beta_8
	cap matrix mat_ESTIMADOS_res[`i',36] == p_beta_0
	cap matrix mat_ESTIMADOS_res[`i',37] == p_beta_1
	cap matrix mat_ESTIMADOS_res[`i',38] == p_beta_2
	cap matrix mat_ESTIMADOS_res[`i',39] == p_beta_3
	cap matrix mat_ESTIMADOS_res[`i',40] == p_beta_4
	cap matrix mat_ESTIMADOS_res[`i',41] == p_beta_5
	cap matrix mat_ESTIMADOS_res[`i',42] == p_beta_6
	cap matrix mat_ESTIMADOS_res[`i',43] == p_beta_7
	cap matrix mat_ESTIMADOS_res[`i',44] == p_beta_8

	local i= `i' + 1

	scalar drop _all

	}
}

set more off

mat list mat_ESTIMADOS_res

preserve
svmat mat_ESTIMADOS_res

rename mat_ESTIMADOS_res1 codigo_res
rename mat_ESTIMADOS_res2 b_cons
rename mat_ESTIMADOS_res3 bres_coltes
rename mat_ESTIMADOS_res4 bres_coltesuvr
rename mat_ESTIMADOS_res5 bres_cocpi_index
rename mat_ESTIMADOS_res6 bres_legatruu
rename mat_ESTIMADOS_res7 bres_colibr_index
rename mat_ESTIMADOS_res8 bres_colcap_index
rename mat_ESTIMADOS_res9 bres_pei_index
rename mat_ESTIMADOS_res10 bres_tcc_rate
rename mat_ESTIMADOS_res11 R2
rename mat_ESTIMADOS_res12 R2a
rename mat_ESTIMADOS_res13 obs
rename mat_ESTIMADOS_res14 summatory_coeffi
rename mat_ESTIMADOS_res15 SSmodel
rename mat_ESTIMADOS_res16 SSresidual
rename mat_ESTIMADOS_res17 SStotal

rename mat_ESTIMADOS_res18 se_cons
rename mat_ESTIMADOS_res19 se_coltes
rename mat_ESTIMADOS_res20 se_coltesuvr
rename mat_ESTIMADOS_res21 se_cocpi_index
rename mat_ESTIMADOS_res22 se_legatruu
rename mat_ESTIMADOS_res23 se_colibr_index
rename mat_ESTIMADOS_res24 se_colcap_index
rename mat_ESTIMADOS_res25 se_pei_index
rename mat_ESTIMADOS_res26 se_tcc_rate

rename mat_ESTIMADOS_res27 t_cons
rename mat_ESTIMADOS_res28 t_coltes
```

```
rename mat_ESTIMADOS_res29 t_coltesuvr
rename mat_ESTIMADOS_res30 t_cocpi_index
rename mat_ESTIMADOS_res31 t_legatruu
rename mat_ESTIMADOS_res32 t_colibr_index
rename mat_ESTIMADOS_res33 t_colcap_index
rename mat_ESTIMADOS_res34 t_pei_index
rename mat_ESTIMADOS_res35 t_tcc_rate

rename mat_ESTIMADOS_res36 p_cons
rename mat_ESTIMADOS_res37 p_coltes
rename mat_ESTIMADOS_res38 p_coltesuvr
rename mat_ESTIMADOS_res39 p_cocpi_index
rename mat_ESTIMADOS_res40 p_legatruu
rename mat_ESTIMADOS_res41 p_colibr_index
rename mat_ESTIMADOS_res42 p_colcap_index
rename mat_ESTIMADOS_res43 p_pei_index
rename mat_ESTIMADOS_res44 p_tcc_rate

keep codigo_res b_cons bres_coltes bres_coltesuvr bres_cocpi_index bres_legatruu bres_co-
libr_index bres_colcap_index bres_pei_index bres_tcc_rate R2 R2a obs summatory_coeffi
SSmodel SSresidual SStotal se_cons se_coltes se_coltesuvr se_cocpi_index se_legatruu
se_colibr_index se_colcap_index se_pei_index se_tcc_rate t_cons t_coltes t_coltesuvr
t_cocpi_index t_legatruu t_colibr_index t_colcap_index t_pei_index t_tcc_rate p_cons p_coltes
p_coltesuvr p_cocpi_index p_legatruu p_colibr_index p_colcap_index p_pei_index p_tcc_rate

save "coef_conrestriccionW_IM_vf2_stat.dta", replace

export excel codigo_res b_cons bres_coltes bres_coltesuvr bres_cocpi_index bres_legatruu
bres_colibr_index bres_colcap_index bres_pei_index bres_tcc_rate R2 R2a obs summa-
tory_coeffi SSmodel SSresidual SStotal se_cons se_coltes se_coltesuvr se_cocpi_index
se_legatruu se_colibr_index se_colcap_index se_pei_index se_tcc_rate t_cons t_coltes
t_coltesuvr t_cocpi_index t_legatruu t_colibr_index t_colcap_index t_pei_index t_tcc_rate
p_cons p_coltes p_coltesuvr p_cocpi_index p_legatruu p_colibr_index p_colcap_index
p_pei_index p_tcc_rate using "coef_conrestriccionW_IM_vf2_stat.xls", firstrow(variables) re-
place

restore
```

Appendix 5. Algorithm employed as an iterative relocation of a *K*-means

The algorithm employed is an iterative relocation of a K-means. If $\mathbf{r_{i,t}} = \boldsymbol{\mu}_{\mathbf{i,t}} + \mathbf{e_{i,t}}$ and $\mathbf{var}(\mathbf{e_{i,t}}) = \boldsymbol{\sigma}_{\mathbf{i}}\boldsymbol{\sigma}_{\mathbf{t}}\mathbf{z_{it}}$, where $\boldsymbol{z_{it}}$is i.i.d. normal for both fund I and *t* with mean 0 and variance 1, then $\boldsymbol{var(e_i)} = \boldsymbol{\sigma_i^2 E(\sigma_t)^2}$ and $\boldsymbol{var(e_t)} = \boldsymbol{\sigma_t^2 E(\sigma_t)^2}$ where $\boldsymbol{\sigma_i}$ and $\boldsymbol{\sigma_t}$ are independent and identically distributed drawing form a population of time-series and across-sectional standard deviation respectively independent of $\boldsymbol{z_{it}}$. As a result, $\boldsymbol{var(e_i)}$, is proportional to $\boldsymbol{var(e_i)} * \boldsymbol{var(e_t)}$. Therefore, it is a simple matter to infer the variance of each time and fund residual as proportional to the marginal time and fund variances in excess of the estimate $\boldsymbol{\mu_{I,t}}$ (See Brown and Goetzman, 1977).

We compute:

$$\boldsymbol{\hat{e}_{i,t} = R_{i,t} + \hat{\mu}_{I,t}} \tag{9}$$

For all funds *I,* we calculate $\boldsymbol{var(\hat{e}_i)}$ and for all *t* we calculate $\boldsymbol{var(\hat{e}_t)}$. Then we compute:

$$\boldsymbol{\hat{\mu}_{I,t} = \sum_{i\in I} \frac{R_{i,t}}{var(\hat{e}_i)} \Big/ \sum_{i\in I} \frac{1}{var(\hat{e}_t)}} \tag{10}$$

This procedure is done to update variance measures. This formula is employed to update centroid mean whenever funds are switched from one cluster to the next, for computational simplicity it is not updated variance measures at each switch. Denote the cluster formed at the *j*th switch as *I*(*j*). Then the criterion function at the *j*th switch is proportional to:

$$\boldsymbol{SSQ_j = \sum_{t=1}^{T} \sum_{I\in Ij} \sum_{i\in I} \frac{\left(R_{i,t} - \hat{\mu}_{I,t}\right)^2}{var(\hat{e}_i) var(\hat{e}_t)}} \tag{11}$$

using the result that $\boldsymbol{var}(\boldsymbol{e_{it}})$ is proportional to $\boldsymbol{var}(\boldsymbol{e_i}) * \boldsymbol{var}(\boldsymbol{e_{it}})$

Once the $\boldsymbol{SSQ_j}$formula is computed, we use the likelihood ratio (*LR*) employed Brown et al (1977) and suggested by Quandt (1960) for each successive decrease in the number of styles. The test statistic for *K* styles (as opposed to *K+1*) styles is:

$$\boldsymbol{LR} = \boldsymbol{T\,m}\left(\mathbf{ln}\,\frac{\boldsymbol{SSQ_k}}{\boldsymbol{T\,m}} - \mathbf{ln}\,\frac{\boldsymbol{SSQ_{k+1}}}{\boldsymbol{T\,m}}\right) \tag{12}$$

where *T* is the number of time periods, *m* the number of funds, and $\boldsymbol{SSQ_k}$ and $\boldsymbol{SSQ_{k+1}}$ are the appropriate heterokedasticity-adjusted sum of squares errors. This statistic should be approximately distributed as $\boldsymbol{X^2}$ with 2*T* degrees of freedom.