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TESIS DOCTORAL/ DOCTORAL DISSERTATION

TRES ENSAYOS SOBRE DIVERSIFICACIÓN Y TECNOLOGÍA
/
THREE ESSAYS ON DIVERSIFICATION AND TECHNOLOGY

RAFFAELE MORANDI STAGNI

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ABSTRACT

The aim of this dissertation is to advance the scholarly understanding of the topics of diversification and technology. The first chapter of the dissertation investigates how diversified firms reallocate internal resources when one of their product business units (BUs) experiences an increase in its exposure to international competition driven by a sharp decrease in trade tariffs. We find that: (1) on average firms tend to fight, i.e. they reallocate resources in favor of the BU affected by the trade shock and away from the rest of BUs that belong to the same firm; (2) under certain conditions the presence of economies of scope generated by scale-free resources negatively moderates the magnitude of the resource redeployment; (3) reallocating resources toward the BU affected by the tariff cut is consistent with value creation.

The second chapter investigates whether firms respond to tougher international competition by investing in technological exploration or exploitation. To obtain exogenous variation in international competition and estimate its causal effect on ambidexterity, we exploit changes in import penetration, which we instrument using exchange rates and scheduled tariffs. We find that tougher international competition causes an increase in technological exploitation and a decrease in technological exploration. Consistently, firms lower their investment in innovation activities and generate patents that are more incremental and therefore receive fewer citations. Our findings suggest that managers should take into account the extent of

competitive pressure in the environment when designing an organizational structure to achieve ambidexterity.

Finally, the third chapter is dedicated to understanding whether the stock market is efficiently pricing the stock of firms that follow a strategy of related diversification from the technological point of view. While consistent with prior research we find that technologically related diversification creates value, related diversifiers appear to be undervalued by investors giving rise to profitable arbitrage opportunities.

INTRODUCCIÓN Y RESUMEN EN EXTENSO

El objetivo de esta tesis doctoral es avanzar la comprensión académica de los temas de diversificación y tecnología. El primer capítulo de la tesis investiga cómo las empresas diversificadas reasignan recursos internos cuando una de sus unidades de negocio experimenta un aumento en su exposición a la competencia internacional impulsada por una fuerte disminución de las tarifas de importación. Encontramos que: (1) en promedio, las empresas tienden a pelear, es decir, reasignan recursos a favor de la unidad de negocio afectada por el shock de tarifas y quitan recursos del resto de unidades de negocio que pertenecen a la misma empresa; (2) bajo ciertas condiciones, la presencia de economías de alcance generadas por recursos scale-free modera negativamente la magnitud del redespliegue de recursos; (3) la reasignación de recursos hacia la unidad de negocio afectada por la reducción de tarifas es consistente con la creación de valor.

El segundo capítulo investiga si las empresas responden a un aumento de la competencia internacional invirtiendo mas en exploración o en explotación tecnológica. Para obtener una variación exógena en la competencia internacional y estimar su efecto causal sobre el nivel de ambidexteridad de la empresa explotamos variaciones en el nivel de penetración de las importaciones, que instrumentamos utilizando las tasas de cambio y las tarifas programadas. Encontramos que una competencia internacional más dura causa un aumento en la explotación tecnológica y una disminución en la exploración tecnológica. Consistentemente, las empresas reducen su inversión en actividades de innovación y generan patentes que son más incrementales y, por lo tanto, reciben menos citas. Nuestros hallazgos sugieren que los gerentes deben tener en cuenta el grado de presión competitiva en el ambiente cuando diseñan una estructura organizacional para lograr ambidexteridad.

En fin, el tercer capítulo está dedicado a comprender si el mercado de valores está valorando eficientemente las acciones de empresas que siguen una estrategia de diversificación relacionada desde el punto de vista tecnológico. Encontramos que la diversificación relacionada desde el punto de vista de la tecnología si crea valor, pero las empresas diversificadas de forma relacionada desde el punto de vista tecnológico parecen estar infravaloradas por los accionistas dando y esto da lugar a oportunidades de arbitraje rentables.

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ABSTRACT

This paper investigates how diversified firms reallocate internal resources when one of their product business units (BUs) experiences an increase in its exposure to international competition driven by a sharp decrease in trade tariffs. We find that: (1) on average firms tend to fight, i.e. they reallocate resources in favor of the BU affected by the trade shock and away from the rest of BUs that belong to the same firm; (2) under certain conditions the presence of economies of scope generated by scale-free resources negatively moderates the magnitude of the resource redeployment; (3) reallocating resources toward the BU affected by the tariff cut is consistent with value creation.

Keywords: Diversification, resources, opportunity cost, competition, internal markets, performance.

CAPÍTULO I:

PELEA O ESCAPA? REDUCCIÓN DE TARIFAS Y REDISTRIBUCIÓN DE RECURSOS EN IMPRESAS DIVERSIFICADAS

RESUMEN

Este articulo investiga cómo las empresas diversificadas reasignan recursos internos cuando una de sus unidades de negocio de productos experimenta un aumento en su exposición a la competencia internacional impulsada por una fuerte disminución en las tarifas comerciales. Encontramos que: (1) en promedio, las empresas tienden a pelear, es decir, reasignan recursos a favor de la unidad de negocio afectada por el shock comercial y lejos del resto de unidades de negocio que pertenecen a la misma empresa; 2) bajo ciertas condiciones, la presencia de economías de alcance generadas por recursos scale-free modera negativamente la magnitud del redespliegue de recursos; (3) la reasignación de recursos hacia la unidad de negocio afectada por la reducción de tarifas es consistente con la creación de valor.

Palabras clave: Diversificación, recursos, costo de oportunidad, competencia, mercados internos, desempeño.

1.1 Introduction

Compared to specialized firms, diversifiers can create value by reallocating scarce resources across the business units (BUs) through which they are competing in different product-markets (Helfat and Eisenhardt, 2004). Levinthal and Wu (2010) label “non scale-free” these resources that cannot be shared at the same time by two distinct BUs, but that can be reallocated across BUs in different time periods by corporate headquarters. Resource redeployment generates inter-temporal economies of scope as long as diversifiers reallocate non-scale free resources from one BU to the others more efficiently than external markets (Williamson, 1975).

The literature up to now has stressed that one of the mechanisms through which value creation happens is the timely reallocation of non scale-free resources from underperforming businesses to more promising opportunities. For example, Lieberman, Lee, and Folta (2017) show with a theoretical model and descriptive statistics from the telecommunication industry that related diversifiers are more likely to speed up exiting from businesses due to redeployment. Wu (2013) reports with hazard and logistic regressions how firms in the cardiovascular medical device segments manifest diversification patterns consistent with the abandon (entry) of sub-markets with a declining (growing) demand.

However, do diversified firms always divert resources from businesses facing environmental challenges? Prior studies addressed the effect of negative demand conditions (Levinthal and Wu, 2010; Lieberman *et al.*, 2017) on companies that are diversified within the same industry (Wu, 2013), we study the effect of competitive shocks on firms that are diversified across industry. While there is no straightforward reason to increase resource investment in product-markets in which the demand is declining, an increase in resource allocation after a competitive shock would serve the purpose of allowing the BU to confront the competitive threat. For example, the BU could make investments to discourage potential entrants by signaling the willingness to engage in a price war (Lieberman and Montgomery, 1988), or it could invest into differentiation to insulate its profit margins from the effect of competition (Fernández-Kranz and Santaló, 2010; Flammer, 2015). Furthermore, the incentives for engaging in defensive strategies are higher for firms that are diversified across industries through separate and independent BUs rather than for firms that are diversified within industry. The cost of developing such an organizational design, associated with specialization and learning economies of the single BU inside a particular market, is unlikely to be recovered unless the firm confronts competitive threats.

To tackle this issue, our paper exploits exogenous changes in product-market competition as the main source of industry variation, and studies how diversifiers can increase (or not) their overall performance by redeploying non scale-free resources across units when one BU shows a deteriorating scenario. In our empirical setting, we investigate the redeployment of financial resources within the firm in the event of a radical change in the industry caused by sharp decreases in import tariff rates. In this respect, we follow prior literature that has reported how tariff changes have a sizable impact on firms' markets and strategies (Flammer, 2015; Frésard, 2010). We chose to examine the reallocation of financial resources because of two reasons. First, financial resources are non scale-free resources since their use in one BU prevents their deployment in another. Second and most important, the allocation of any non scale-free resource towards a BU should be positively associated to the amount of financial resources channeled towards it[1].

From the empirical point of view, it is worth to note that our diff-in-diff design allows us to directly observe resource reallocation and to test the simultaneous significance of both effects, the in- and out-flow. Prior studies of resource reallocation were either theoretical (Helfat and Eisenhardt, 2004; Levinthal and Wu, 2010) or were inferring resource reallocation by the effect of the activity on firm's behavior and performance (Lieberman *et al.*, 2017; Wu, 2013). Our findings provide evidence that after an increase in international competition due to tariff shocks, headquarters reallocate their financial resources towards the BU affected, and away from the rest of the BUs.

Given that diversified firms can also benefit from the synergies generated by the contemporaneous sharing of scale-free resources, like for example a general purpose technology (Miller, 2006; Penrose, 1959; Rumelt, 1982; Silverman, 1999; Teece, 1982), we also include in our analysis the potential substitution effect between scale-free and non scale-free resources hypothesized by Sakhartov and Folta (2014) and Lieberman *et al.* (2017). This substitution effect describes the existence of a trade-off between the benefits of achieving synergies and the advantages conferred by resource redeployments.

[1] If the corporate headquarter allocates more skilled personal to reinforce the R&D effort of the affected BU, or if it decides to assign it more marketing power in terms of resources and personnel, this should be translated into higher financial expenses in the business unit impacted by the trade shock and we should be able to track it with our measures of financial resource allocation.

Firms embracing more technological (i.e. scale-free) related diversification should show stronger positive correlations in the performances of their BUs, and thus they should give less autonomy to the distinct BUs (Helfat and Eisenhardt, 2004; Hill, Hitt, and Hoskisson, 1992). Lower autonomy levels means that there is less need to allocate resources to the individual BUs given a competitive threat, with the consequence that resource redeployment towards the BU in trouble will be less necessary. We find that the extent of technological relatedness of the BU affected by the shock negatively moderates the size of the reallocation, but only when tariff cuts do not negatively affect the value of technology.

Finally, we also report that the amount of resources transferred toward the BU affected by competition has a positive impact on overall firm performance, meaning that we are observing a rational, value creation strategy. To give a first idea of the size of the effect, we estimate that on average diversified firms increase their allocation of resources to the BU directly affected by a trade tariff cut by 3.1 percent of their average segment assets. In turn, an increase in resource allocation of this amount after a tariff shock, translates into a 1.7 percent gain in the market-to-book value and a 5.4 percent gain in market-to-sales value at corporate level. These findings are consistent with the idea that the common pockets are used to finance individual BU strategies designed to compete effectively in a more hostile environment (Frésard, 2010).

This paper contributes to the literature that studies the antecedents and the performance consequences of resource redeployment in diversified firms. First, we show how firms may optimally chose to step up investment in the BU negatively affected by a shock rather than reallocating resources towards other businesses. In so doing, we provide evidence that in a context characterized by a competitive (and not demand) shock, and by a diversifiers organized in independent business units that operate in different industries, firms opt for fight, compared to the flight option highlighted by previous works (Helfat and Eisenhardt, 2004; Wu, 2013). Then, our study contains one of the first robust empirical evidence of the substitution effect between inter-temporal and intra-temporal economies of scope (Lieberman *et al.*, 2017; Sakhartov and Folta, 2014). We show that when technology is a valuable competitive asset in the sector affected by the tariff cut, then technological relatedness negatively moderates resource reallocation.

Finally, our findings also confirm that an important part of the diversifiers' advantage resides in the reallocation processes, and not only in resource synergies (Markides and Williamson, 1996; Teece, 1982). More precisely, the reallocation of non-scale free resources in internal markets is a value creation mechanism for diversified firms, at least under the novel contingencies that we highlight.

1.2 Introducción

En comparación con las empresas especializadas, las empresas diversificadas pueden crear valor mediante la reasignación de recursos escasos entre las unidades de negocio (UN) a través de las cuales compiten en diferentes mercados de productos (Helfat y Eisenhardt, 2004). Levinthal y Wu (2010) etiquetan como "*non scale-free*" estos recursos que no pueden ser compartidos al mismo tiempo por dos UN diferentes, pero que pueden ser reasignados entre las UN en diferentes períodos de tiempo por la sede corporativa. El redespliegue de recursos genera economías de alcance intertemporales siempre que las empresas diversificadas reasignen recursos libres de escala de una UN a las otras de manera más eficiente que los mercados externos (Williamson, 1975).

La literatura hasta ahora ha enfatizado que uno de los mecanismos a través del cual ocurre la creación de valor, es la reasignación de recursos *non scale-free* de negocios con bajo rendimiento a oportunidades más prometedoras. Por ejemplo, Lieberman, Lee y Folta (2017) muestran con un modelo teórico y estadísticas descriptivas de la industria de las telecomunicaciones que las empresas diversificadas de manera relacionada tienen más probabilidades de acelerar la salida de malos negocios gracias a la reasignación interna de los recurso. De forma parecida Wu (2013) encuentra atreves de regresiones logísticas que las empresas que producen dispositivos médicos cardiovasculares manifiestan patrones de diversificación consistentes con el abandono (entrada) de los submercados con una demanda en declive (creciente).

Sin embargo, ¿las empresas diversificadas siempre desvían los recursos de UN que se enfrentan a desafíos ambientales? Estudios previos abordaron el efecto de las condiciones de demanda negativa (Levinthal y Wu, 2010; Lieberman et al., 2017) sobre empresas que están diversificadas dentro de la misma industria (Wu, 2013), en este estudio en vez examinamos el efecto de los choques competitivos en empresas que están diversificadas en industrias distintas. Si bien no existe una razón clara para aumentar la inversión en recursos en mercados en los que la demanda está disminuyendo, un aumento en la asignación de recursos después de un choque competitivo serviría para permitir que la unidad de negocios se enfrente a la amenaza competitiva. Por ejemplo, la UN podría realizar inversiones para desalentar a los posibles entrantes señalando la voluntad de empezar una guerra de precios (Lieberman y Montgomery, 1988), o podría invertir en diferenciación para aislar sus márgenes de beneficio del efecto de la competencia (Fernández-Kranz y Santaló, 2010; Flammer, 2015). Además, los incentivos para involucrarse en estrategias defensivas son mayores para empresas que están diversificadas en industrias diferentes a través de unidades de negocio separadas e independientes en comparación con empresas que diversificadas dentro de la industria. Es poco probable que dichas empresas recuperen el costo de desarrollar el diseño organizacional, asociado con economías de especialización y aprendizaje de la UN dentro de un mercado particular, a menos que la empresa se enfrente a amenazas competitivas.

Para abordar este problema, nuestra investigación explota cambios exógenos en la competencia en el sector de una de las UN de la empresa y estudia cómo las empresas pueden aumentar (o no) su rendimiento general redistribuyendo recursos *non scale-free*. En particular investigamos la redistribución de los recursos financieros dentro de la empresa en caso de un cambio radical en la industria causado por fuertes disminuciones en los aranceles de importación. En este sentido, seguimos la literatura previa que ha informado cómo los cambios tarifarios tienen un impacto considerable en los mercados y las estrategias de las empresas (Flammer, 2015; Frésard, 2010). Elegimos examinar la reasignación de recursos financieros por dos razones. Primero, los recursos financieros no son recursos *non scale-free* ya que su uso en una UN impide su inversión en otra. En segundo lugar, la asignación de cualquier recurso *non scale-free* hacia una UN debe estar asociada positivamente a la cantidad de recursos financieros canalizados hacia ella[2].

Desde el punto de vista empírico, vale la pena señalar que nuestro diseño diff-in-diff nos permite observar directamente la reasignación de recursos y probar el significatividad simultánea de ambos efectos, el del flujo de entrada y el del flujo salida. Los estudios previos de reasignación de recursos son en mayoría teóricos (Helfat y Eisenhardt, 2004; Levinthal y Wu, 2010) o infieren la reasignación de recursos por el efecto de la actividad en el comportamiento y en el rendimiento de la empresa (Lieberman et al., 2017; Wu, 2013). Nuestros hallazgos proporcionan evidencia de que después de un aumento en la competencia internacional debido a los shocks tarifarios, la sede central reasigna sus recursos financieros hacia la UN afectada por el shock y lejos del resto de las UN.

Dado que las empresas diversificadas también pueden beneficiarse de las sinergias generadas por el hecho de que su UN utilizan simultáneamente recursos *scale-free*, como por ejemplo una tecnología de propósito general (Miller, 2006, Penrose, 1959, Rumelt, 1982, Silverman, 1999, Teece, 1982), también incluimos en nuestro análisis el efecto de sustitución potencial entre la

[2] Si la sede corporativa asigna personal más capacitado para reforzar el esfuerzo de I + D de la UN afectada, esto debería traducirse en mayores gastos financieros en la unidad de negocio afectada por el shock de tarifas y deberíamos ser capaces de observar la redistribución de recursos con nuestras medida de asignación de recursos financieros.

presencia de sinergias y la redistribución de recursos hipotetizado por Sakhartov y Folta (2014) y Lieberman et al. (2017).

Este efecto de sustitución describe la existencia de una compensación entre los beneficios de lograr sinergias y las ventajas conferidas por redespliegue de recursos. Las empresas que adopten una diversificación más tecnológica (es decir, *scale-free*) deberían mostrar correlaciones positivas más fuertes entre rendimiento de sus UN, y por lo tanto deberían dar menos autonomía a las UN específicas (Helfat y Eisenhardt, 2004; Hill, Hitt y Hoskisson, 1992). Los niveles de autonomía más bajos significan que hay menos necesidad de asignar recursos a las UN individuales dada una amenaza competitiva, con la consecuencia de que el redespliegue de recursos hacia la UN en apuros será menos necesario. Encontramos que el grado de relación tecnológica de la UN afectada por el shock modera negativamente el tamaño de la reasignación, pero solo cuando las reducciones arancelarias no afectan negativamente el valor de la tecnología.

Finalmente, también informamos que la cantidad de recursos transferidos hacia la UN afectada por la competencia tiene un impacto positivo en el desempeño general de la empresa, lo que significa que estamos observando una estrategia racional de creación de valor. Para dar una primera idea del tamaño del efecto estimamos que, en promedio, las empresas diversificadas aumentan su asignación de recursos a la unidad de negocios directamente afectada por una reducción de aranceles comerciales de un 3.1 por ciento de sus activos de segmento. A su vez, un aumento en la asignación de recursos de este monto después de un shock tarifario se traduce en una ganancia de 1.7

por ciento en el *market-to-book ratio* y un aumento de 5.4 por ciento en el *market-to-sales ratio* a nivel corporativo. Estos hallazgos son consistentes con la idea de que los bolsillos comunes se utilizan para financiar estrategias individuales de UN diseñadas para competir efectivamente en un ambiente más hostil (Frésard, 2010).

La presente investigación contribuye a la literatura que estudia los antecedentes y las consecuencias del redespliegue de recursos en empresas diversificadas. En primer lugar, mostramos cómo las empresas pueden optar de manera óptima por aumentar la inversión en la unidad de negocio afectada negativamente por un shock en lugar de reasignar recursos hacia otras UN. Al hacerlo, proporcionamos evidencia de que en un contexto caracterizado por un shock competitivo (y no de demanda) y por empresas diversificadas organizadas en unidades de negocios independientes que operan en diferentes industrias, las empresas optan por la lucha, en comparación con la opción de escapar destacada por el anterior trabajos (Helfat y Eisenhardt, 2004; Wu, 2013). Además, nuestro estudio contiene una de las primeras pruebas empíricas sólidas del efecto de sustitución entre las economías de alcance intertemporal e intratemporal (Lieberman et al., 2017; Sakhartov y Folta, 2014). Mostramos que cuando la tecnología es un activo competitivo valioso en el sector afectado por el recorte tarifario, la relación tecnológica en UN modera negativamente la reasignación de recursos.

Finalmente, nuestros hallazgos también confirman que una parte importante de la ventaja de las impresas diversificadas reside en los procesos de reasignación de recursos y no solo en las sinergias (Markides y Williamson, 1996; Teece, 1982). Más precisamente, la reasignación de recursos *non scale-free* en los mercados internos es un mecanismo de creación de valor para empresas diversificadas, al menos bajo las nuevas contingencias que destacamos.

1.3 Theory Review

1.3.1 Resource reallocation in the multi-business firm

Understanding within firm resource allocation is fundamental to shed light on the mechanisms of value creation or value destruction of diversified firms; only when diversified firms are more efficient than external markets in allocating resources across businesses they have a reason to persist and thrive (Williamson, 1975). Otherwise, diversified firms can be regarded as an outcome of managerial opportunism that creates inefficient companies that could only survive in environments with little or biased competitive conditions (Giroud and Mueller, 2011).

From a bird-eye view, the strategic option to withdraw resources from one BU and allocate them to another depicts a value creating mechanism that is different from the mainstream concept of resource synergy (Rumelt, 1982; Silverman, 1999; Teece, 1982). Synergies are generated by the contemporaneous sharing of resources with unlimited capacity. Resource reallocation instead is possible only in the presence of assets that have an opportunity cost (labeled non scale-free resources; Levinthal and Wu, 2010).

Studies addressing resources reallocation have led to several interesting findings about the dynamics of value creation in diversified firms. In particular, the focus of the literature has been on understanding how diversifiers use resource redeployment in response to negative market conditions (Anand and Singh, 1997; Levinthal and Wu, 2010; Lieberman *et al.*, 2017; Wu, 2013). Levinthal and Wu (2010) and Wu (2013) for example demonstrate that in mature markets, where the growth in firm's capabilities exceeds the growth in demand, profit-maximization might entail sacrificing the performance of part of the organization. If diversifying firms internally transfer non scale-free resources from their existing BUs to a new operating product-market, it is likely that the performance of the existing BUs will be negatively affected despite the overall profitability gain. Likewise, Lieberman *et al.* (2017) show that the value of a strategy of related diversification might reside in a firm's ability to exit from businesses that fail to meet demand expectations with high speed and little sunk cost.

These studies established that the optimal response for firms operating in environments experiencing adverse demand conditions is that of diverting resources away from the affected product-market. Our study instead addresses the effect of competitive shocks. In particular, we investigate the effect of significant increases in competition that affect one of the BUs of a diversified firm on the resource reallocation that follows.

As an illustration of the effect of competition, consider the case of MagneTek. In 1995, MagneTek experienced a significant increase in competition in its "Lighting Products" market (SIC code 3612), which in 1994 accounted for 42 percent of the firm's sales. This increase in competition came in the form of a 51 percent reduction of the import tariff rate applied to the products of foreign competitors and it is reflected in the Company's 10-K report of 1996 (MagneTek Inc., 1996): *"During fiscal 1996, the Company experienced lower demand and a significant deterioration in operating results in [light product business], due largely to a substantial reduction in utility related incentive programs and increased competition. […] The Company conducted a review and analysis of actions […] to reflect costs associated with repositioning operations."* (1996 10-K report, https://www.sec.gov). The words "repositioning operations" for MagneTek are associated with a redistribution of resources, but the open theory question is toward which BU? At least in the case of Magnetek, resources were reallocated toward the lighting products BU after the tariff shock. The increase in resource allocation served the purpose of financing the consolidation of operations and the adoption of practices aimed at achieving a better response to customers' needs, better quality, and lower defect rates (e.g. Demand Flow Technology and Six Sigma).

As the Magnetek example illustrates, unlike environmental changes that involve a decline in demand, competitive shocks are susceptible of both increasing and decreasing the marginal value of investments in a sector (Aghion *et al.*, 2005; Raith, 2003). This could in turn produce both a reallocation toward or away from the affected BU. A reallocation of resources away from the troubled BU would serve the purpose of recovering the profitability of the re-deployable assets by exploiting their use in protected market niches. This "flight" alternative is the value creation mechanism that previous literature has associated with resource redeployment in response to negative demand conditions (Levinthal and Wu, 2010; Lieberman *et al.*, 2017; Wu, 2013). In the case of competition however, corporate headquarters can also opt for an increase in resource allocation towards the troubled BU with the purpose of fostering the BU's ability to compete. This "fight" alternative implies channeling more resources, rather than less, to preserve and increase the future profitability of the BU affected by the shock. An increased allocation can serve the purpose of allowing the BU to engage in preemptive actions that increase the entry barriers to the sector, or that signal to potential entrants the willingness to engage in aggressive behavior (e.g. a price war; Lieberman and Montgomery, 1988). Further, increased resource allocation is also necessary to pursue both investments aimed at reducing cost (Scherer and Ross, 1990), and achieve product differentiation with the purpose of insulating the profit margin from the adverse effect of competition (Aghion *et al.*, 2005; Fernández-Kranz and Santaló, 2010; Flammer, 2015).

Both the "fight" and "flight" alternatives are consistent with value creation. However, notwithstanding this tension at the theoretical level, we expect to observe on average a "fight" behavior in our empirical context (i.e. a reallocation toward the business unit affected by the competitive shock) for the following two reasons. First, there is substantial empirical evidence showing how access to internal resources is linked to better performance in competitive environments (e.g. Deb, David, and O'Brien, 2017; Frésard, 2010; Haushalter, Klasa, and Maxwell, 2007). For example Deb, David, and O'Brien (2017) show that companies operating in competitive sectors obtain higher market valuations when they have substantial cash reserves. Likewise, Fresard (2010) finds that access to internal resources after a competitive shock produced by a trade liberalization is linked to market share gains at the expenses of rivals. Second, the firms in our sample are diversified across industries through separate and independent BUs designed to address the specificities of different market environments. The investment of developing such an organizational design, associated with specialization and learning economies of the single BU inside a particular market, would probably be compromised if firms choose to flight. Hence, under these contingencies, we hypothesize:

H1: Diversifiers will reallocate non scale-free resources to the business units affected by an increase in competition.

1.3.2 The substitution effect between scale-free and non scale-free resources

The recognition of resource reallocation as a value creating mechanism separated from synergy opens the question of how the two interact with each other in the determination of firm's value. Sakhartov and Folta (2014) and Lieberman *et al.* (2017) hypothesize that resource reallocation and synergy are interdependent and to a certain extent substitute mechanisms that increase the value of a diversified company. Considering that synergies are obtained when resources are contemporaneously shared across BUs, resource withdrawal involved in reallocation compromises the returns from synergies. Vice-versa, given that reallocation requires subtracting resources from one or more product-markets, pursuing synergies compromises value creation through reallocation.

To understand the rationale behind this statement it is important to examine the linkage between diversification strategy and organizational structure. The diversification literature has long established that being diversified in industries that have the potential to achieve economies of scope by transferring or sharing resources is not enough to increase firm value. Firms need to organize accordingly and design a corporate organization and incentive structure that allows the potential synergies to become real (Barney, 2001; Barney and Mackey, 2005; Markides and Williamson, 1996). In particular, Hill *et al.* (1992) and Helfat and Eisendhardt (2004) show how firms that follow a related diversification strategy should optimally introduce organization practices at the corporate level that promote coordination among business units. This coordination is imperative to realize the value creating properties of related diversification, and it requires that the corporate office retains some control over the functions common to the BUs. This is also a direct consequence of the fact that synergies increase the positive correlations of performance across BUs. On the contrary, this centralization is not required in firms that follow an unrelated diversification strategy since in these cases each BU must have autonomy with regard to operating decisions, so that BU directors can be held accountable for BU financial results (Hill *et al.*, 1992). In other words, since there are no synergies to be managed, BU managers should have incentives to maximize the individual value of the BU without any considerations about the joint value of the performance of other BUs (Santaló and Kock, 2009).

This optimal association between centralization (autonomy) and related (unrelated) diversification strategies indicates different resource redeployment practices will be needed as a reaction to a shock in any given BU. Companies that have a related diversification strategy and that are optimally more centralized will reallocate less resources towards the BU affected by the shock since more competitive levels decisions are taken at the corporate level. Hence we hypothesize:

H2: The presence of synergies between the business unit affected by the competitive shock and the rest of the business units of the firm, negatively moderates the amount of non scale-free resource reallocation toward the business units affected by the competitive shock.

1.4 Data & Methodology

1.4.1 Data sources

We use the import tariff data compiled by Feenstra (1996), Feenstra, Romalis and Schott (2002), and Schott (2010) to capture variations in the intensity of foreign competition faced by U.S. domestic firm. Each product category imported in the U.S. is identified through a ten-digit HS code (Harmonized System) as defined by the World Custom Organization (WCO). Feenstra (1996) and Schott (2010) develop mappings that allow for the aggregation of HS product data into four-digit SIC codes (Standard Industry Classification), this is our definition of industry. The resulting data is available for the period 1974–2005 only for the manufacturing SIC (SIC 2000–3999), therefore our analysis is restricted to manufacturing business units. There are originally 507 industries in the database; in 482 of these are operating diversified firms included in the COMPUSTAT Segment database.

For each industry–year we calculate the *ad-valorem* tariff rate as the ratio between the duties collected by U.S. customs and the Free-on-Board value of imports. Tariff rates tend to fluctuate from year to year. However, the average tariff change is typically small and not economically significant (Flammer, 2015). To distinguish minor tariffs fluctuation from important tariff reductions, we compare the tariff change, as calculated for a given industry-year, with the average tariff change for the same industry calculated on the whole sample period. Specifically, we follow Frésard (2010), Frésard and Valta (2016), and Flammer (2015), and consider a negative tariff change as a tariff cut only if it exceeds by three times the average tariff variation for its industry. We ignore the tariff variations occurred between 1988 and 1989 because of a change in the coding of the imports. To ensure that what we are observing are not transitory tariff fluctuations, we further require that the tariff cuts are not preceded or followed by equivalently large tariff increases. Finally, to make sure that the identified events have some economic significance, we require the tariff rate in the year before the tariff cut to be at least one percent.

We are interested only in those events starting from 1977, as the COMPUSTAT Segment database starts in 1976 and as we require at least one year of data prior to the tariff cut. The application of these criteria produces 214 tariff cut events, the first occurring in 1977 and the last occurring in 2005. These events pertain to 170 unique industries. Figure 1.1 shows that the events occur over the entire duration of the sample period. This characteristic helps to ensure that our results are not driven by time-specific confounding factors such as the economic cycle. From Figure 1.1 is possible to identify two large waves of trade liberalization. The first took place in the period between 1980 and 1982 and it is the direct result of the ratification of the General Agreement on Tariffs and

Trade (GATT) Tokyo round, and of the implementation of the U.S. Trade Agreement Act (TAA) in 1979. The second wave occurred in the early nineties and it is produced by the ratification of the Free Trade Agreement (FTA) between the U.S. and Canada in 1989, followed by the ratification of the North American Free Trade Agreement (NAFTA) between the U.S., Canada, and Mexico in 1994. On average the tariff cuts represent a 41 percent reduction of the tariff rate, from an average tariff rate of 6.7 percent in the year prior to the event to an average tariff rate of 4.2 percent in the year after the event.

********************Please insert Figure 1.1 about here**********************

A simple analysis on single segment firms further confirms the economic impact of our negative shocks. On average, single segment firms operating in a treated four-digit SIC code report a decrease of 7.8 percent in their market-to-book value (from 2.19 to 2.02) between the three years after and the three years before the negative tariff variation. Moreover, three year after the trade shock around 15 percent of the single segment firms have disappeared from Compustat. Finally, in a separate analysis available upon request, we study whether tariff reductions have a positive effect on the amount of total industry sales in the product-market affected[3]. This positive effect of industry sales could happen if the trade shock is associated as well with more export opportunities in international markets. We find no impact of the trade shock on total industry sales. This is, the sharp decrease in tariffs rate does not seem to increase

[3] We estimate sector fixed-effect regression with year controls that test the effect of tariff cuts both on the internal demand and on the total demand faced by U.S. producers. We calculate a sector's internal demand as the natural log of the value of shipments plus imports, minus exports. We calculate a sector's total demand as the natural log of the value of shipments plus exports. Results are never significant.

market expansion opportunities for the treated BUs and on the contrary it is just a sharp increase in the strength of international competition levels.

We obtain firm- and BU-level financial and accounting data from the Standard & Poor’s Compustat database. To compute our measure of scale-free resource relatedness we use the National Bureau of Economic Research (NBER) patent database (Hall, Jaffe, and Trajtenberg, 2001). The NBER patent database covers the period 1976-2006. It contains detailed information about the patents granted to firms by the U.S. Patent and Trademark Office (USPTO), the type of technology contained in the patents (patent class) and the changes in the ownership of the patents through time.

1.4.2 Methodology

We adopt a difference-in-difference design based on the 214 tariff cuts already identified. We form two samples, each composed by BUs belonging to diversified firms affected by a tariff cut and control BUs belonging to diversified firms not affected by a tariff cut. The first sample, which we term “*Treated BUs & Treated Firm Sample*” is formed by BUs operating in an industry that is undergoing a tariff cut. The second sample instead, which we term “*Non-Treated BUs & Treated Firm Sample*”, is formed by those BUs belonging to a diversified firm that is experiencing a tariff cut in one of its businesses, but that are not directly affected by a tariff cut in their industry. These two groups of BUs are matched with control BUs following the procedure detailed below. Our treatment variable, *Tariff Cut*, is a dummy variable that takes the value of 1 when, depending on the analysis, either the firm or the BU is experiencing a tariff cut while it takes a value of 0 otherwise.

In our context, the purpose of the diff-in-diff design is to compare the resource reallocation process of firms with a treated BU with the resource reallocation process of firms not affected by tariff cuts. Note that our design based on two samples requires an increase in allocation to the BU subject to the tariff cut to be statistically significant vis-à-vis a corresponding statistically significant decrease in allocation to the rest of the BUs of the firm. Therefore to claim that we are observing resource reallocation we need to obtain statistically significant results in two analyses performed on two different samples[4].

Matching

We match each BU in our two samples with a control observation based on the year and based on a set of industry, firm and BU characteristics. First, we require each control observation to operate in an industry similar to that of its corresponding treated observation. The fact that our treatments are defined at the four-digits SIC level, prevents us from matching observations based on the narrowest definition of industry. Instead, we require matched observations to operate in the same two-digits SIC industry and to serve primarily the same type of customers (Business-to-Business vs Business-to-Consumer). We rely on Sharpe (Sharpe, 1982) and Lev *et al.* (Lev, Petrovits, and Radhakrishnan, 2010) for the partition of SIC industries according to the primary type of customer that they serve. This approach addresses two potential concerns. On one side, we need treated and matched observations to operate in industries

[4] This design drastically reduces the probability of a false rejection of the null (type I error). In fact, if we obtain statistical significance with opposite signs at the 10 percent confidence level in the two samples the probability that what we are observing is actually due to chance is of 1 percent (10% X 10%).

with similar logics and similar dynamics. On the other side however, we also need to keep our pool of potential matches sufficiently large for us to select an observation based on firm and BU characteristics. Requiring control BUs to operate in the same three-digits SIC sector of the treated observations would likely affect our ability to fulfill the second requirement.

Next, out of the remaining pool of candidates, we pick the closest neighbor based on a set on BU and firm characteristics: *BU Resource Allocation*, *BU Size*, *Firm Size*, *Firm Cash*, *Firm Leverage, Firm Number of Segments*. We measure all these characteristics using data coming from COMPUSTAT. In particular, *BU Resource Allocation* is the value of resource allocation over segment assets; both *BU Size* and *Firm Size* are calculated as the log of sales; *Firm Cash* is the log of cash and short-term investments; *Firm Leverage* is the ratio of debt over total assets; *Number of Segments* is simply the count of firm's segments. The first five variables are measured as averages in the three years before the treatment. *Firm's Number of Segments* is the count of firm segments in the year of the tariff shock. The closest neighbor is selected based on the Mahalanobis distance calculated on the six matching characteristics[5]. We follow Flammer (2015) in requiring that treated and match observations have at least available data in the year before and the year after the treatment for them to be included in the sample.

We selected the matching variables based on their likelihood to influence the level of resource allocation received by a BU. In particular, matching

[5] We avoid the same control observations to be selected multiple times using a randomization procedure. For each treated observation we calculate its three nearest neighbors using the "mahapick" command in Stata 12. Whenever the closest match is selected multiple times for different treated observations we randomize between these in order to choose which observation is going to be assigned its second closest match. The command that we use is "mahaselectunique" in Stata 12.

observation on the pre-treatment value of *Resource Allocation* reduces the noise due to the correlation of the dependent variable with its own lagged values. Matching on the *Number of Segments* makes sure that the firms have a similar number of BUs competing for resources. *Firm Size* and *BU Size* influence the ability of the firm to considerably change the level of investment in the BU. *Firm Cash* and *Firm Leverage* capture the ability of the firm of using internal liquidity or additional debt to increase resource allocation to a BU.

*******************Please insert Table 1.1 about here*********************

The application of these criteria produces a *Treated BUs & Treated Firm Sample* with a total of 1598 observations (799 treated observations and 799 control observations), and a *Non-Treated BUs & Treated Firm Sample* with a total of 2494 observations (1247 treated observations and 1247 control observations).

Dependent Variables

The most easily re-deployable resource that a diversified firm has available is certainly cash. A transfer in cash is also a proxy for the reallocation of other classes of non scale-free resources. For example, an increase in personnel in one BU is accompanied with an increase in salary expenses.

To capture variations in spending across the BUs of a diversified firm we focus on the difference between cash invested and cash generated. A tariff cut in the operating product-market of a focal BU can affect its level of sales and thus profitability. We assume that the level of spending of a focal BU partially depends on its level of financial resource generation; granted, we follow Billet & Mauer (2003) in the calculation of our dependent variable, *Resource Allocation*.

In particular, *Resource Allocation* is defined as the difference between a BU capital expenditure and its own After-Tax Cash Flow (ATCF). Therefore, for every given sample year, we calculate *Resource Allocation* for BU *i* of firm *j* in year *t* as:

$$Resource\ \ Allocation_{i,t} = CAPEX_{i,t} - ATCF_{i,t} \tag{1}$$

Where $CAPEX_{i,t}$ and $ATCF_{i,t}$ are respectively BU *i*'s reported capital expenditure and BU *i*'s after-tax cash flow in year *t*. $ATCF_{i,t}$ is calculated as follows:

$$ATCF_{i,t} = (EBIT_{i,t} - I_{i,t})(1 - T_{i,t}) + D_{i,t} \tag{2}$$

Where $EBIT_{i,t}$ is BU *i*'s reported earnings before interest and taxes, $D_{i,t}$ is BU *i*'s reported depreciation and amortization expense and, $I_{i,t}$ and $T_{i,t}$ are respectively BU *i*'s imputed interest expense and BU *i*'s imputed tax rate[6].

More than on the total value of *Resource Allocation*, we are interested in the change in *Resource Allocation* caused by the shock. Therefore, for each treated and control observation we compute the difference between the BU's average *Resource Allocation* after the treatment minus the average *Resource Allocation* before the treatment. We follow Flammer (2015) in using a window of three years for the calculation of the averages. Finally, to reduce the influence of outliers, we deflate the difference by the total segment assets calculated as the average in the three years before the treatment. Therefore, our final dependent variable is calculated as follows:

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[6] The imputed interest expense, $I_{i,t}$, is calculated as the product of BU *i*'s reported sales and the median ratio of interest expense to sales calculated on all the focused firms operating in business unit *i*'s industry. The imputed tax rate, $T_{i,t}$, is represented by the median ratio of income taxes due to pre-tax income calculated on all the focused firms operating in BU *i*'s industry. We define business unit *i* industry as the narrowest SIC grouping returning at least five focused firms (Billett and Mauer, 2003).

$$\Delta Resource\ Allocation_{i,t} = \left(\sum_{x=t+1}^{t+3} \frac{R.Allocation_{i,x}}{3} - \sum_{x=t-1}^{t-3} \frac{R.Allocation_{i,x}}{3} \right) / \sum_{x=t-1}^{t-3} \frac{BUassets_{i,x}}{3} \quad (3)$$

Our measure is in theory defined also for single segment firms. We estimate regressions to control for whether tariff cuts affect resource allocation in this group of competitors and we find no results. On average it appears that focused firms are not able to significantly alter the difference between resource expenditure and resource generation after an increase in international competition.

For what concerns our measures of performance, we follow the diversification literature and compute both the firm's *Market-to-Book* value and the firm's *Market-to-Sales* value (e.g. Berger and Ofek 1995, Lang and Stulz 1994). For our purpose market measures of performance are better than accounting measures of performance because they are forward looking. In fact, it could take several years for the consequences of a change in corporate investment policy to be reflected in the income statement of the firm. Further the initial impact of investments on accounting returns can be negative if the investment expenses are not capitalized.

We calculate the firm's *Market-to-Book* value as the ratio between the market value of the firm and the book value of the assets. We calculate the firm's *Market-to-Sales* value as the ratio between the market value of the firm and firm's total sales. The firm's market value in turn, is calculated as the sum of the firm's market capitalization and of the book value of the firm's debts.

Again, as for our measure of *Resource Allocation*, we are interested in the change in performance caused by our treatment. Therefore, we calculate our final dependent variables as the difference between the average values of the multiples in the three years after the tariff cut minus the average value of the multiples in the three years before the tariff cut.

Technological relatedness

We include as independent variable the degree of *Technological Relatedness* between the BU affected by the shock and the rest of the BUs of the firm. In particular, we measure the level of technological relatedness of BU *i*'s based on the total amount of cross-citation between patents granted to companies operating in sector *i* and patent granted to companies active in the rest of the operating product-markets of the focal firm. Cross-citations measures have been widely used to capture the extent of inter-organizational knowledge flows (Mowery, Oxley, and Silverman, 1996; Schildt, Keil, and Maula, 2012). The calculation of our measure follows a similar logic to capture the potential for intra-organizational knowledge sharing between the BUs of the firm. We consider cross-citations between a sector pair as a proxy for the extent to which the two sectors share a similar technological base. We argue that the more similar the technological base of the sectors in which two different BUs of the firm operate, the more likely the firm will benefit by having its BUs share their knowledge. This in turn should lead the firm to carry out the R&D relevant for the BUs at the corporate level (Hill *et al.*, 1992).

As a first step in the calculation, we attribute to every patent in the NBER database a four-digits SIC code using the operating-sector of the patent owner as reported in COMPUSTAT[7]. Next, we compute a three-years rolling sum of the total amount of cross-citation between each industry pair. We assume that, the more the patents assigned to companies operating in two different four-digits SIC codes cite each other, the more the two industries are technologically related. The calculation is the following:

$$CrossCit_{A,B,t} = \sum_{t-3}^{t-1} C_{A\rightarrow B} + C_{B\rightarrow A} \tag{4}$$

Where "$CrossCit_{A,B,t}$" is the total amount of cross-citation between the Sector "A" – Sector "B" pair as calculated in year "t", "$C_{A\rightarrow B}$" is the total number of times that patents granted in a given year to companies operating in the SIC sector "A" cite patents granted to companies operating in the SIC sector "B", and "$C_{B\rightarrow A}$" is the opposite.

Next, having estimated the level of the relatedness of each four-digits SIC pair, we calculate the level of relatedness of BU *i* by doing a weighted average by segment sales of the cross-citation between operating sector *i* and the rest of the operating sector of the firm. We take the natural logarithm of the resulting measure to reduce the influence of outliers. Therefore:

$$Technological\ Relatedness_{i,t} = \ln \sum_{\substack{Y=1 \\ Y\neq i}}^{N} CrossCit_{i,Y,t} * \frac{s_{i,Y,t}}{\sum_{\substack{X=1 \\ X\neq i}}^{N} s_{i,X,t}} \tag{5}$$

Were $Technological\ Relatedness_{i,t}$ is the estimate of BU *i*'s technological relatedness in year *t*, *N* are the sectors in which the diversified firm to which BU *i* belongs is operating, and $s_{i,Y,t}$ ($s_{i,X,t}$) is the sum of sales of operating segment

[7] If a patent has multiple owners we divide equally the weight of the patent between the operating sectors of the owners. If a patent belongs to a diversified firm we divide the weight of the patent proportionally between the operating sectors of the firm by segment sales.

i and operating segment *Y* (*X*) in year *t*. This measure is intended to capture the extent to which BU *i* shares a common technological base with the rest of the BUs of the firm. We compute it based on the total cross-citation between patents granted by the USPTO in the three years before the shock.

Control variables

We include ten control variables in our analysis. Five controls coincide with our matching variables. In particular we control for: firm's size, firm's cash, firm's number of segments, firm's leverage and BU's size. The reasons for the inclusion of these variables and the procedure for their calculation is addressed in the section explaining the matching procedure. Further, we control for the percentage difference in the total size of the market between the period before and after the tariff cut. Market size is defined as the total sales of the firms operating in a given SIC4. The inclusion of this variable controls for whether observed reallocation is driven by changes in demand in the operating sector affected by the shock.

We also control by the *Relative Profitability* of the BU affected by the tariff shock in comparison to that of the rest of the BUs of the firm. We expect that if the BU subject to the tariff cut is relatively more profitable, the firm will be more likely to defend it from competition. We capture the *Relative Profitability* of BU *i*'s, in comparison with that of the rest of the BUs of the firm, through the difference between BU *i*'s ROA and the weighted average ROA of the rest of the BUs of firm *j* (Billett and Mauer, 2003). We calculate ROA as the ratio between a BU's EBIT and its reported total assets. Our measure of relative profitability is then computed as follows:

$$Relative\ Profitability_{i,t} = ROA_{i,t} - \sum_{\substack{a=1 \\ a \neq i}}^{N} ROA_{a,t} * \frac{BUassets_{a,t}}{Fassets_{j,t} - BUassets_{i,t}} \tag{6}$$

Where N is the number of segments in which the firm *j* is operating, $BUassets_{a,t}$ and $BUassets_{i,t}$ are respectively the total assets reported by BU *a* and the total assets reported by BU *i*, and $Fassets_{j,t}$ is the total assets reported by firm *j* to which all the BUs belong.

Finally, we control by the *Relative Size* of the BU affected by the tariff shock. *Relative Size* is computed as the ratio of BU sales to total firm sales. *Relative Size* is both a proxy for power of the division affected by the tariff cut and a test for the presence of behavioral biases (Bardolet, Fox, and Lovallo, 2011) that could influence resource reallocation decisions. If power issues are present, we expect that BUs with a higher relative size will obtain a comparatively higher endowment of resources after the competitive shock. If instead corporate managers have a tendency toward naïve diversification[8] than, after an increase in competition, BUs that are comparatively bigger will receive less resources; vice-versa for BUs that are comparatively smaller.

For *Relative Profitability* and *Relative Size* we control for both the main effect and the interaction with the tariff cut in the analyses on the *Treated BUs & Treated Firm Sample* since both variables could have a more important role in resource reallocation after changes in the tariff rates. For the analyses on the *Non-Treated BUs & Treated Firm Sample* instead, the interaction is not

[8] Naïve diversification refers to the general tendency of managers to disregard differences in size, profitability and growth opportunities of the operating BUs and therefore to spread capital equally across them. Bardolet *et al.* (2011) show that to a certain extent this behavioral bias can account for the phenomenon of cross-subsidization.

necessary as the value the value of the two variables is set to zero for the control group.

Table 1.1 reports descriptive statistics about the matching variables and the control variables for both samples and for each group of treated and control BUs. In particular, the table reports the mean value, the median value and the value of the 25th and 75th percentile. In the two samples treated and control observations are almost identical, both in the mean and in the distribution. We argue that similarity along these dimensions ensures that the control BUs are representative of what would have happened to our dependent variable in the absence of an import tariff cut. Figure 1.2 is a graphic depiction of trend in average resource allocation in the years between t-3 and t+3, where t is the year of the tariff cut, for both samples and for both the treatment and control groups. As is possible to see, the treatment and control groups have similar trends in both samples in the years between t-3 and t-1 further confirming the validity of our matching procedure. The sudden variation that occurs in both samples between t-1 and t+1 instead, is evidence that the economic impact of the tariff cut is concentrated around the years immediately before and immediately after the treatment.

*****************Please insert Figures 1.2.a & 1.2.b about here*********************

General Estimation Model

To measure the effect of a tariff cut on the level of resource allocation received by those BUs that are affected by it we estimate the following regression on the *Treated BUs & Treated Firm Sample*:

$$\Delta Resource\ \ Allocation_{i,t} \qquad (7)$$

$$= \alpha_t + \ \beta_1 \times Tariff\ \ Cut_{i,t} + \beta_2 \times Technological\ Relatedness_{i,t}$$

$$+ \beta_3 \times Tariff\ Cut_{i,t} \times Technological\ \ Relatedness_{i,t} + \gamma' \mathrm{X}_{i,t}$$

$$+ \epsilon_{i,t}$$

Where α_t are year fixed effects, *Tariff Cut* is our treatment dummy variable equal to one if the observation belongs to the treatment sample and to zero if it belongs to the control sample, *Technological Relatedness* is our independent variable calculated as described above, ϵ is the error term, and *X* is a vector of control variables which includes five of the six characteristics used for the matching (firm's size, firm's cash, firm's number of segments, firm's leverage and BU's size, we exclude BU's resource allocation because the depended variable is the difference between the period after and the period before the tariff cut), a variable controlling for the difference in the total size of the market between the period before and after the tariff cut, *Relative Profitability*, *Relative Size*, and the interaction of these last two variables with the tariff cut.

To measure the effect of a tariff cut on the level of *Resource Allocation* received by those BUs that are not directly affected by it we estimate the following regression on the *Non-Treated BUs & Treated Firm Sample*:

$$\Delta Resource\ Allocation_{i,t} \qquad (8)$$

$$= \alpha_t + \ \beta_1 \times Tariff\ Cut_{i,t} + \beta_2$$

$$\times Technological\ \ Relatedness\ BUTC_{i,t} + \gamma' \mathrm{X}_{i,t} + \epsilon_{i,t}$$

Where *Technological Relatedness BUTC* (BU Tariff Cut) is defined for treated observations as the value of *Technological Relatedness* of the BU of the firm that is affected by the tariff cut while it takes a value of zero for the control group. We set the value for the control group to zero because control observations are selected from firms that are not experiencing a tariff cut. Considering that also the tariff cut dummy is zero for the control group any interaction with *Technological Relatedness BUTC* would be equal to *Technological Relatedness BUTC*. Accordingly, in this sample we also control for *Relative Profitability BUTC* and *Relative Size BUTC* (instead of *Relative Profitability*, *Relative Size* and interactions).

We cluster standard errors at the two-digits SIC industry level. The coefficients of interest are β_1 and β_3 for the analyses on the *Treated BUs & Treated Firm Sample* and β_1 and β_2 for the analyses on the *Non-Treated BUs & Treated Firm Sample*. We expect each pair of coefficients to take opposite signs in the two samples if an increase in competition triggers an exchange of resources.

***********************Please insert Table 2.2 about here************************

1.5 Results

Table 2.2 presents the results of the analyses on the *Treated BUs & Treated Firm Sample* together with the results of the analyses on the *Non-Treated BUs & Treated Firm Sample*. In all regressions, the dependent variable is the change in total resource allocation three years after compared to three years before the treatment deflated by segment assets. The table contains eight models. In model 1, 2, 5, and 6 the regressions include only the tariff cut dummy, *Technological Relatedness*, and the interaction between *Technological Relatedness* and the tariff cut dummy when needed. In model 3, 4, 7, and 8 we include year fixed effects and our controls variables. All the regressions have clustered standard errors at the two-digits SIC level.

Note that the models estimated on the *Non-Treated BUs & Treated Firm Sample* do not include interactions. This is because in this sample the values of our independent variable *Technological Relatedness,* and of two of our controls*,* *Relative Profitability* and *Relative Size*, are for treated observations not their own values of technological relatedness, relative profitability, and relative size, but those of the BU of the firm that is undergoing a tariff cut in its operating product-market. Considering that control observations are selected from firms that do not experience any tariff cut, for the control group we set the corresponding value of the independent variables to zero. Since the value of both the tariff cut dummy and the independent variables is equal to zero for the control group, any interaction between the two is equal to the independent variable of the interaction.

We start by examining the main effect that competition has on the resource reallocation activity. According to Hypothesis 1 we expected tariff cuts to cause a reallocation of resources from the BUs operating in stable market conditions to the BUs affected by the shock. The results from the analyses support the hypothesis. The coefficient of the tariff cut dummy at the BU level is positive and significant in the analyses on the *Treated BUs & Treated Firm Sample*. Correspondingly, the coefficient of the tariff cut dummy at the firm level is negative and significant in the analyses on the *Non-Treated BUs & Treated Firm Sample*. In particular, in the analyses on the *Treated BUs & Treated Firm Sample*, the coefficient lies between 0.031 (p-value < 0.05) in the model including only the tariff cut dummy, and 0.067 (p-value < 0.05) in the model including control variables and year fixed effects. In the analyses on the *Non-Treated BUs & Treated Firm Sample* instead, the coefficient lies between -0.018 (p-value < 0.05) in the model including only the tariff cut dummy, and -0.059 (p-value < 0.01) in the model including control variables and year fixed effects. If we consider the models that include only the tariff cut dummy, this implies that on average diversified firms increase their allocation of resources to the BUs directly affected by a tariff cut by 3.1 percent of their average segment assets. On the contrary, diversified firm correspondingly decrease the allocation of resources to the rest of the operating BUs by 1.8 percent of their average segment assets. Note that the reduction in resource allocation in the BUs not affected by the tariff cut is less than the corresponding increase in resource allocation in the BUs affected by it. This is consistent with the fact that firms in our sample have an average of 3.26 BUs and thus, they can spread the burden of financing across more than one unit.

Before examining the results for H2 we briefly comment on the effect of two of our control variables. Both the relative profitability and the relative size of the BUs subject to the tariff cut appear to influence the magnitude of the resource reallocation that follows the shock. In particular, the results support our expectation that *Relative Profitability* positively moderates resource redeployment. The higher the returns generated by the BU subject to the shock in comparison to those generated by the rest of the firm's portfolio of businesses, the more the firm will redeploy resources to defend the BU. On the contrary, the moderation of *Relative Size* is negative. In the case of *Relative*

Size we did not have clear expectations, since the variable can be both a proxy that tests for internal power dynamics and behavioral biases (Bardolet *et al.*, 2011). Nevertheless, the results from the analyses are consistent with the presence of behavioral biases in our empirical context. Business units that are large in comparison to the total size of the firm, experience a comparatively smaller increase in resource allocation after the shock.

Next, we examine the effect of technological relatedness on reallocation. The results from the main analyses support only partially Hypothesis 2 and the idea that the presence of technological synergies negatively moderates resource reallocation. While the coefficient of *Technological Relatedness BUTC* in the analyses on the *Non-Treated BUs & Treated Firm Sample* is positive and significant as expected (in the full model coeff. = 0.009, $p<0.05$), the interaction between *Technological Relatedness* and *Tariff Cut* in the analyses on the *Treated BUs & Treated Firm Sample* is never significant.

One possible explanation for these partial findings is that technological relatedness only matters for resource reallocation when investing in technology is a valuable mean of differentiation for the BU affected by the tariff cut. In this case, if the firm is a related diversifier with a centralized R&D function the reaction will happen at the corporate level and no reallocation of resources will take place. If instead technology is not particularly valuable in confronting the new competitive threat, than the BU will invest in other means of differentiation (e.g. CSR, customer service or plant capacity) and in order to do so it will need a higher amount of resource allocation from the corporate headquarter. The analyses contained in Table 1.3 test this idea. We first separate sectors in which tariff cuts increase the value of technology from sectors in which tariff cuts decrease the value of technology[9]. Then we proceed to the formation of one *Treated BUs & Treated Firm Sample* and one *Non-Treated BUs & Treated Firm Sample* for each type of sector using the standard procedure. As expected the negative moderation of technological relatedness is present only when tariff cuts increase the value technology (coeff. = -0.025, p<0.1 in the *Treated BUs & Treated Firm Sample*; coeff. = 0.014, p<0.05 in the Non-*Treated BUs & Treated Firm Sample*). In particular, this negative moderation means that if the BU affected by the tariff cut operates in a sector in which competition increases the value of technology, and its value of relatedness is equal to the median value of the *Treated BUs & Treated Firm Sample*, then resource allocation to it will decrease by 0.8 percent of segment assets while resource allocation to the rest of the BUs of the firm will increase by 0.5 percent of segment assets.

**********************Please insert Tables 1.3 & 1.4 about here*********************

Finally, we turn to the analysis of the impact of tariff shocks on the overall firm performance to check if this reallocation process is a value creation or destruction activity. In these regressions, the independent variables are the dummy that identifies treated and control firms, the amount of cash transfer

[9] To accomplish this task we estimate regressions that test the effect of the interaction between a firm's patent stock and the tariff cut on the firm's Market-to-Book value. These regressions are estimated only on single segment firms and for every two-digits SIC code. The form of the regression models is the following:

$$MktBook_{j,t} = \alpha_t + \beta_1 \times T.Cut_t + \beta_2 \times N.Patents_{j,t} + \beta_3 \times T.Cut_t \times N.Patents_{j,t}$$

Where $N.Patents_{j,t}$ is the logarithm of the total number of patents granted on a five years window, and $T.Cut_t$ is a dummy that takes the value of one in the years following the tariff cut. Each regression is estimated on a timespan of ten years (five before the tariff cut and five after the tariff cut) and it includes control variables (log of assets, the ratio of EBIT over sales, and the ratio of CAPEX over sales), firm fixed-effects and clustered standard errors at the firm level. We estimate the regressions at the two-digits SIC level for two reasons. First, the sample size of each regression was in many cases too small to obtain reliable estimates at four- and three-digits SIC level. Second, considering that we match observation based on the two-digit SIC industry, estimating the effect of competition on the value of technology also at the two-digits SIC level increases the comparability between treated and matched observation.
If the coefficient of β_3 is positive, then tariff cuts increase the value of technology as a competitive resource, vice versa if β_3 is negative. Due to space limitations we are not able to include descriptive statistics about all the samples, however additional information is available from the authors upon request.

(positive or negative) received by the BU subject to the tariff cut, and the interaction of both variables plus standard controls. The size of the sample (1,372 observations) is smaller than that of the *Treated BUs & Treated Firm Sample* because some diversified firms do not have valid data in Compustat for the calculation of the market multiples. To keep the sample balanced when a firm does not have valid data we also delete the corresponding matched observation. Table 1.4 displays the results of this regression with our two distinct measures of performance, the firm's *Market-to-Book* and the firm's *Market-to-Sales*. In both models, we find that the interaction of the tariff cut dummy and the resource allocation received by the BUs subject to the shock has a positive and statistically significant coefficient (for *Market-to-Book* coeff. = 0.47, $p<0.01$; for *Market-to-Sales* coeff. = 1.71; $p<0.10$). This supports the hypothesis that we are observing a value creating activity. In particular, as noted above, on average a tariff cut produces an increase in *Resource Allocation* equal to 3.1 percent of the segment assets. An increase in allocation of this size after the tariff shock in turn produces a 1.7 percent gain in the *Market-to-Book* value and of 5.4 percent gain in the *Market-to-Sales* value in comparison to the scenario in which the increase in allocation happens in normal market conditions.

To conclude, we note that the main effect of the resource transfer is always negative and statistically significant. This is consistent with the sizable literature that has discussed how the presence of agency problems might turn the internal market for resources from a value creation into a value destruction tool (Ozbas and Scharfstein, 2010; Scharfstein and Stein, 2000). If we analyze together the main effect and the interaction of resource transfer with the trade shock dummy we get a richer picture on the impact of internal resource markets on firm performance. In the absence of a trade shock the average impact of resource transfer is negative and consistent with the existence of a dark side of internal capital markets (Ozbas and Scharfstein, 2010; Scharfstein and Stein, 2000). However when one of the BUs suffers a strong negative competitive shock as the one we are examining in this paper the net impact of resource transfer on firm performance becomes positive if we use the coefficients of the *Market-to-Sales* regression (1.71>1.60) and six times lower if we take the regression with *Market-to-Book* as dependent variable (-0.560+0.468=-0.092).

1.6 Discussion and conclusions

This paper examines the effect of an increase in competition after a trade shock on the redistribution of non scale-free resources within diversified firms. We draw on a sample in the manufacturing industry for the period 1976-2006 of 799 treated Business Units (BUs), and of 1247 non-treated BUs in companies with a treated BU, with the corresponding matching control sample. We use the difference between capital expenditures and cash flow as a proxy to capture non scale-free resource reallocation. Our results complement the findings of the literature on diversification, performance, and firm resources (Helfat and Eisenhardt, 2004; Levinthal and Wu, 2010; Lieberman *et al.*, 2017; Sakhartov and Folta, 2014; Wu, 2013) because they speak of a positive and significant effect of competition on resource reallocation toward the BU affected by the shock, and of a negative moderation of scale-free resources relatedness on resource redeployment.

Our findings about the interaction between scale-free resource relatedness and resource redeployment provide evidence supporting the view that the two mechanisms of value creation are interdependent (Lieberman *et al.*, 2017; Sakhartov and Folta, 2014). Nevertheless, they also speak about the importance of considering in the analysis the effect that market shocks have on the value of the synergies in place. In fact, we found that the negative moderation is only present in sectors in which the tariff cut positively influences the value of technology. In sectors where the opposite is happening the effect of scale-free resource relatedness is not significant.

Our finding that tariff cuts cause a reallocation of resources toward the business unit affected instead, highlight how the direction of the resource reallocation following a negative market shift critically depends on the type of shock. Prior work established that the optimal reaction for diversifiers experiencing a decline in demand in one of their operating product-markets consists in shifting non scale-free resources away from it (Levinthal and Wu, 2010; Lieberman *et al.*, 2017; Wu, 2013). On the contrary, we find that diversifiers react to competitive shocks by increasing their commitment to the affected product-market. This finding is consistent with prior studies showing that competition causes firms to invest into differentiation (Aghion *et al.*, 2005; Fernández-Kranz and Santaló, 2010; Flammer, 2015) and with evidence showing that access to internal resources in competitive environments is particularly beneficial for firm performance (Deb *et al.*, 2017; Frésard, 2010).

Nevertheless, we acknowledge that our results might be limited to firms that are diversified across industry as we expect the sunk cost of investment to be particularly high for this group of competitors. Firms that are diversified across industry in fact, afforded both the cost of investing in the specific assets and competencies that are necessary to operate in markets that do not share a common logic, and the cost of building the formal organization that is necessary to govern the relationships between BUs. These cost are unlikely to be recovered if the firm decides to scale back its commitment from the product-market affected by competition. Both Wu (2013) and Lieberman *et al.* (2017) instead investigate companies that are diversified within the same industry (cardiovascular medical devices and telecommunication) were arguably the fungibility of assets across market opportunities is higher. This in turn allows firms to reconsider their asset configuration with reduced redeployment cost. Future research could address whether our findings about the effect of competition on reallocation hold in a context of intra-industry diversification, and whether the findings of Wu (2013) and Lieberman *et al.* (2017) about the effect of declining demand on reallocation hold in a context of diversification across industry.

However, is the reallocation of resources to BUs affected by competition a rational choice? We do test the efficiency hypothesis inside our sample and we find that reallocating resources toward BUs affected by tariff cuts contributes to value creation. It is important to note that our study does not question the results of the agency literature that has studied internal capital markets (Ozbas and Scharfstein, 2010; Scharfstein and Stein, 2000). Consistent with the presence of agency problems we do find that resource reallocation is on average associated with a decrease in overall firm performance. On average the amount of BU cash transfer is associated to a lower firm market-to-book and market-to-sales ratio unless this was a response to a competitive shock. In this case, the net impact is either positive or close to zero. Notwithstanding this observation, our findings highlight the importance of considering the contingencies under which resources reallocation creates and destroys value. We believe this is critical, as the internal market for resources is certainly one of the most important features that separates diversified firms from single segment competitors (Williamson, 1975). An understanding of its inner working could contribute to the reconciliation of the mixed results obtained by the literature examining the linkage between diversification and performance (Berger and Ofek, 1995; Santaló and Becerra, 2008; Villalonga, 2004).

Finally, our findings are also interesting for the literature studying competitive dynamics (Smith, Ferrier, and Ndofor, 2001). The fact that diversified firms internally transfer resources across their operating sectors suggests that exogenous increases in competition in sectors populated by diversified firms could generate stronger competitive reactions from incumbents. On the other hand, sectors that are not directly affected could experience a decrease in competitive pressure due to the decreased resource allocation to BUs operating in stable market conditions. This deduction has important policy implications when diversifiers own dominant positions in different markets; a competitive shock in one market could be translated to another only because these markets are inside the portfolio of a same (dominant) company. Antitrust experts should indeed think well about the antecedents of competitive pressures that could be more endogenous than thought. A similar concern was recently expressed by the business press (Wall Street Journal, 2017).

We conclude by acknowledging that our study also suffers from some limitations. First, our study analyzes resource reallocation processes of firms that are already diversified, with several synergies and coordination costs already in place. Second, our empirical test of non-scale-free resource reallocation is limited to financial resources. Although we believe that our results should be generalizable to other fungible categories of non scale-free resources, we are unable to explicitly consider them in our empirical analysis. Our study also does not take into account agency explanations for internal resource transfer. While this is out of the scope of our paper, we do believe that studying the effect of compensation and of elements of firm's structure influencing internal power struggle on resource reallocation, would definitely enrich our knowledge of how diversified firms allocate resources (Rajan, Servaes, and Zingales, 2000).

1.7 References

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Figure 1.1: Number of tariff cut events by year

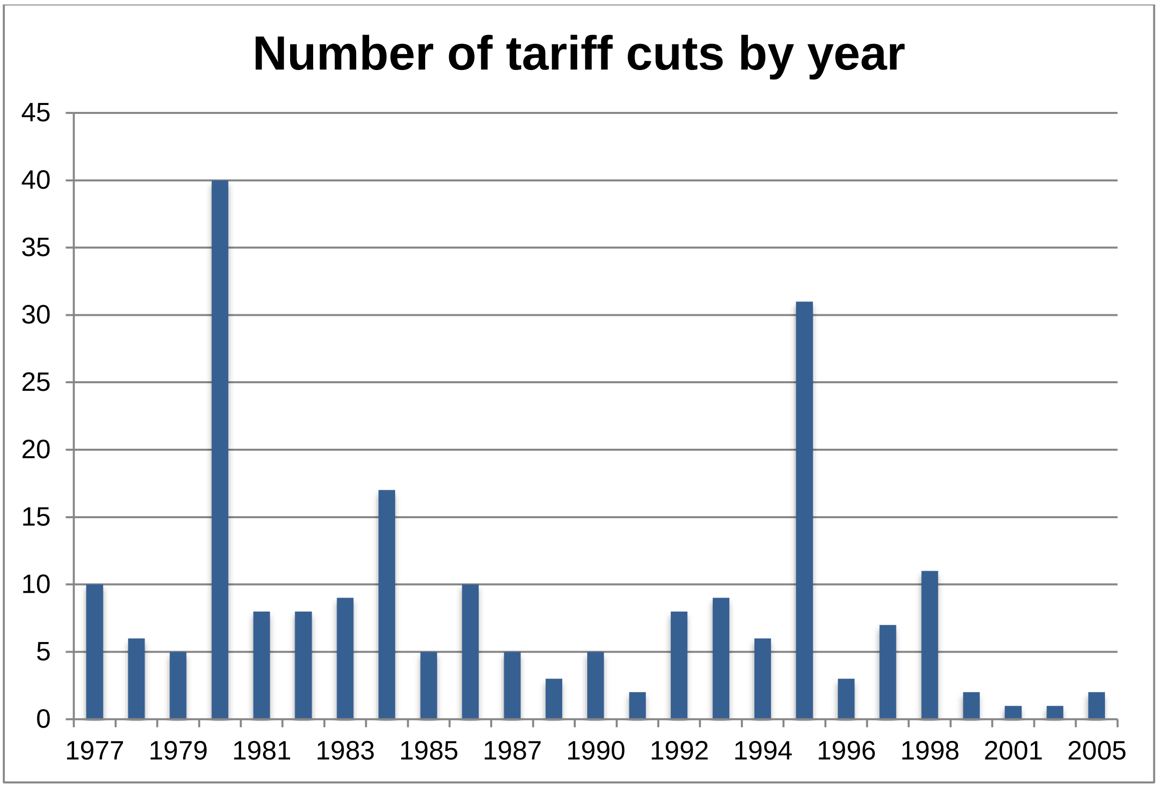

Figure 1.2.a: Trend in Resource Allocation over assets in the "Treated BUs & Treated Firm Sample"

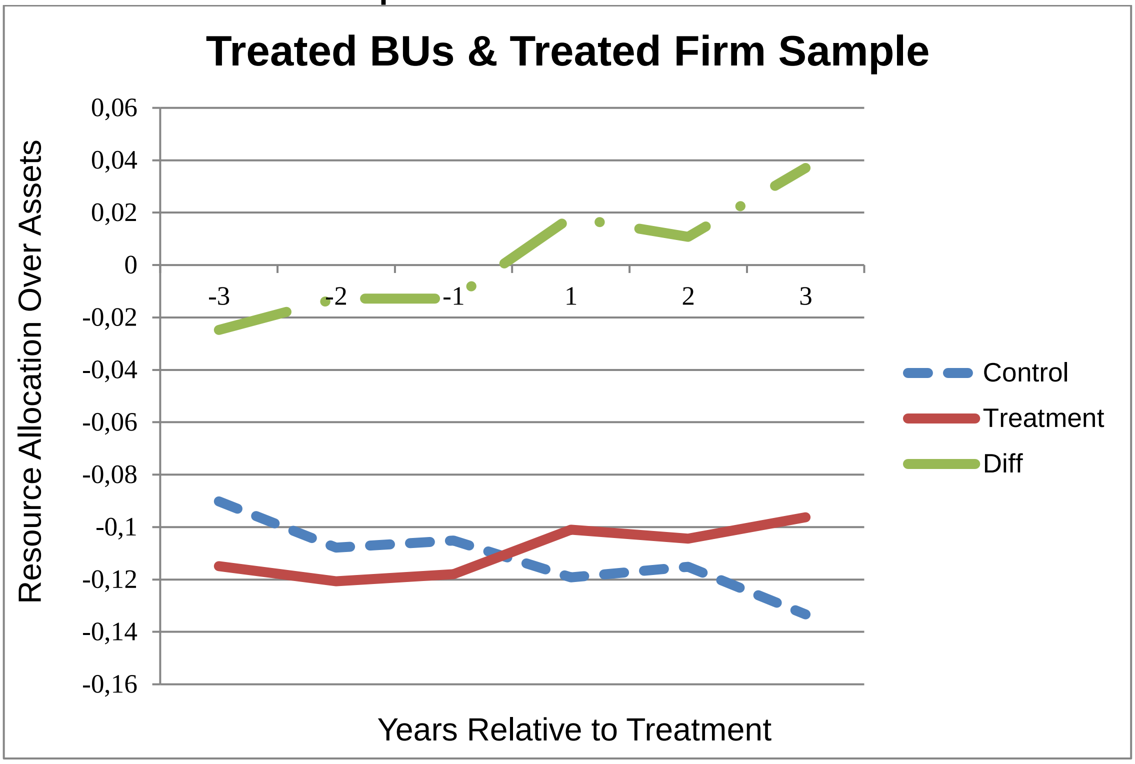

Figure 1.2.b: Trend in Resource Allocation over assets in the "Non-Treated BUs & Treated Firm Sample"

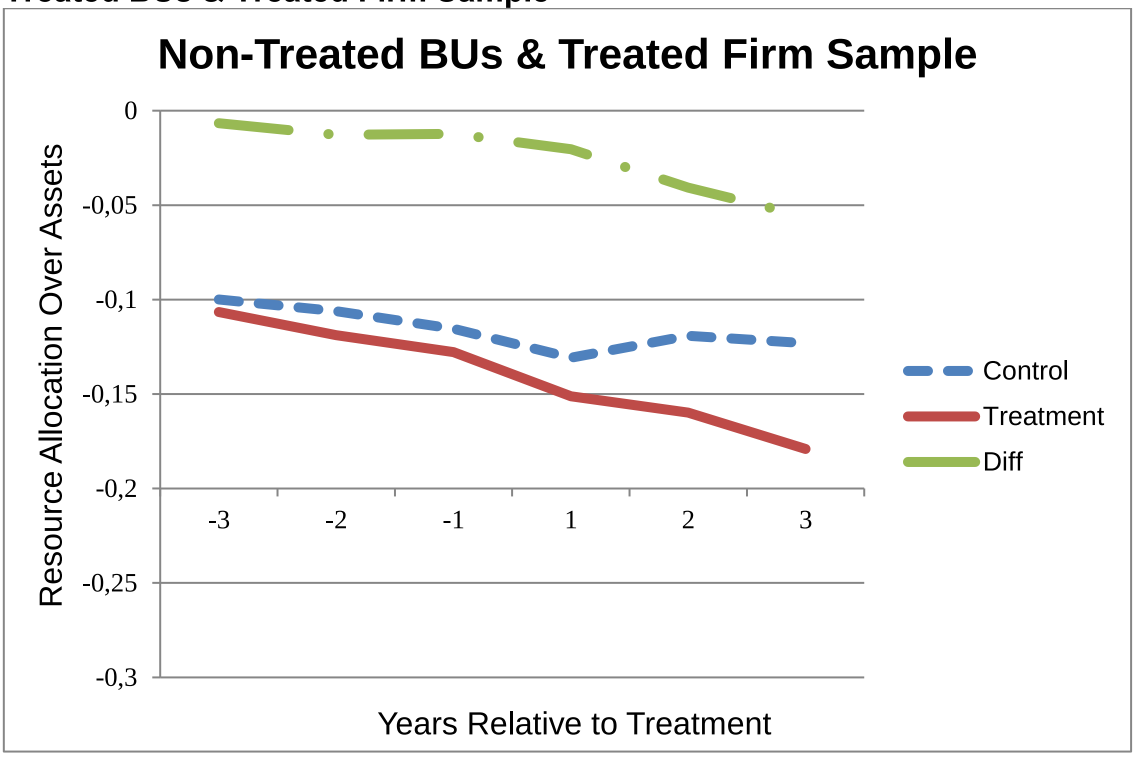

Table 1.1: Samples descriptive

		N. Obs.	Mean	Min	Max	SD	25p	50p	75p
TREATED BUs & TREATED FIRM SAMPLE									
Matching variables									
Resource Allocation	Treatment	799	-0.11	-6.65	1.18	0.34	-0.17	-0.09	-0.02
	Control	799	-0.10	-1.34	0.95	0.15	-0.15	-0.09	-0.03
BU Sales (log)	Treatment	799	4.22	0.09	10.08	1.98	2.70	4.33	5.61
	Control	799	4.31	0.12	9.48	1.90	2.96	4.37	5.61
Firm Sales (log)	Treatment	799	5.51	0.91	10.99	2.04	3.92	5.56	7.16
	Control	799	5.53	0.86	10.97	1.96	4.00	5.56	6.95
Firm Cash (log)	Treatment	799	2.69	0.00	9.65	1.85	1.21	2.42	4.08
	Control	799	2.68	0.00	9.69	1.78	1.19	2.47	3.88
Firm Leverage	Treatment	799	0.56	0.08	2.26	0.21	0.44	0.55	0.65
	Control	799	0.55	0.10	1.42	0.17	0.44	0.54	0.63
Number of BUs	Treatment	799	3.31	2	10	1.35	2	3	4
	Control	799	3.21	2	10	1.24	2	3	4
Other controls									
Diff in Mkt. Size	Treatment	799	0.59	-0.95	17	1.44	-0.10	0.31	0.78
	Control	799	6.48	-0.98	4650	164.5	-0.14	0.35	0.76
Rel. Profitability	Treatment	799	0.04	-3.38	11.58	0.65	-0.09	0.01	0.11
	Control	799	0.01	-5.36	6.52	0.37	-0.08	0.01	0.09
Relative Size	Treatment	799	0.36	0.00	1.00	0.26	0.14	0.30	0.56
	Control	799	0.37	0.01	1.00	0.25	0.16	0.31	0.55
Independent variables									
Tech. Relatedness	Treatment	799	1.08	0.00	8.12	1.50	0.00	0.33	1.77
	Control	799	1.07	0.00	7.83	1.55	0.00	0.27	1.64
NON-TREATED BUs & TREATED FIRM SAMPLE									
Matching variables									
Resource Allocation	Treatment	1247	-0.10	-2.50	4.44	0.22	-0.17	-0.09	-0.03
	Control	1247	-0.10	-1.77	0.87	0.14	-0.15	-0.09	-0.03
BU Sales (log)	Treatment	1247	4.63	0.06	10.91	2.00	3.15	4.72	6.01
	Control	1247	4.58	0.13	10.37	1.87	3.17	4.64	5.84
Firm Sales (log)	Treatment	1247	6.03	0.91	10.99	2.06	4.67	6.19	7.46
	Control	1247	5.86	0.45	10.65	1.91	4.41	6.09	7.27
Firm Cash (log)	Treatment	1247	3.08	0.00	9.65	1.97	1.49	2.99	4.37
	Control	1247	2.88	0.00	8.87	1.78	1.43	2.79	4.15
Firm Leverage	Treatment	1247	0.57	0.12	2.50	0.21	0.45	0.55	0.65
	Control	1247	0.56	0.13	1.73	0.17	0.45	0.55	0.64
Number of BUs	Treatment	1247	3.90	2	10	1.54	3	4	5
	Control	1247	3.57	2	10	1.34	3	3	4
Other controls									
Diff. in Mkt. Size	Treatment	1247	1.17	-0.98	828	23.47	-0.12	0.26	0.76
	Control	1247	0.55	-0.99	29	1.61	-0.09	0.31	0.76
Rel. Profit. BUTC	Treatment	1247	0.00	-4.81	7.89	0.45	-0.09	-0.01	0.09
Relative Size BUTC	Treatment	1247	0.30	0.01	0.98	0.23	0.12	0.24	0.43
Independent variables									
Tech. Rel. BUTC	Treatment	1247	1.23	0.00	8.12	1.56	0.02	0.57	1.95
PERFORMANCE ANALYSIS SAMPLE									
Market-to-Book	Treatment	686	1.06	0.17	7.75	0.74	0.64	0.84	1.25
	Control	686	1.08	0.08	19.37	1.08	0.65	0.83	1.22
Market-to-Sales	Treatment	686	1.00	0.07	20.55	1.33	0.43	0.67	1.10
	Control	686	1.06	0.08	44.11	2.29	0.46	0.67	1.08

Table 1.2: Main results

This table contains the results of regression analyses performed on the sample of BUs directly affected by a tariff cut in their operating product-market (*Treated BU & Treated Firm Sample*), and on the sample of BUs that operate stable market conditions but that belong to a diversified firm that it is experiencing a tariff cut in one of its operating product-markets (*Non-Treated BU & Treated Firm Sample*). Both groups of BUs are matched with corresponding control BUs belonging to diversified firms that are not affected by tariff cuts. A description of the control variables and of the procedure for their calculation is available in the method section. Note that the values of *Technological Relatedness*, *Relative Profitability*, and *Relative Size* in the analyses on the *Non-Treated BU & Treated Firm Sample* are those of the BUs of the firm that are experiencing a tariff cut (BUTC), the value for the control group is set to zero. No interaction is necessary.

Dependent Variable: ΔResource Allocation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Treated BU & Treated Firm				*Non-Treated BU & Treated Firm*			
Tariff Cut	0.031 (0.017)	0.018 (0.163)	0.067 (0.011)	0.057 (0.058)	-0.018 (0.032)	-0.026 (0.023)	-0.059 (0.000)	-0.069 (0.000)
Technological Relatedness		-0.004 (0.218)		-0.000 (0.946)		0.007 (0.095)		0.009 (0.037)
Tech. Relatedness X T. Cut		0.012 (0.405)		0.009 (0.342)				
Controls								
Relative Profitability			0.045 (0.318)	0.045 (0.318)			-0.126 (0.002)	-0.126 (0.002)
Rel. Profitability X T. Cut			0.208 (0.002)	0.207 (0.002)				
Relative Size			0.039 (0.700)	0.045 (0.651)			0.139 (0.007)	0.135 (0.010)
Rel. Size X T. Cut			-0.122 (0.023)	-0.122 (0.025)				
BU Size			0.030 (0.249)	0.028 (0.301)			0.016 (0.006)	0.015 (0.008)
Firm Size			-0.057 (0.115)	-0.056 (0.123)			-0.005 (0.460)	-0.005 (0.426)
Firm Cash			0.028 (0.022)	0.027 (0.022)			-0.002 (0.486)	-0.003 (0.337)
Number of Segments			-0.001 (0.931)	0.000 (0.999)			0.000 (0.925)	0.000 (0.911)
Firm Leverage			0.044 (0.514)	0.044 (0.510)			0.030 (0.319)	0.029 (0.326)
Market Difference			0.000 (0.230)	0.000 (0.240)			0.000 (0.050)	0.000 (0.037)
Year Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES
N. Observations	1,598	1,598	1,598	1,598	2,494	2,494	2,494	2,494
Adj. R sq.	0.000	0.000	0.062	0.061	0.001	0.001	0.038	0.039

Note: Exact p-values in parentheses

Table 1.3: The effect of scale-free resource relatedness on resource reallocation depending on whether tariff cuts increase or decreases the value of technology

This table separates industries in which tariff cuts had a positive effect on the value of technology from industries in which the opposite occurred. For each type of industry we proceed to the formation of a *Treated BU & Treated Firm Sample* and a *Non-Treated BU & Treated Firm Sample* using the standard matching procedure described in the method section. A description of the control variables and of the procedure for their calculation is also available in the method section. Note that the value of *Technological Relatedness* in the analyses on the *Non-Treated BU & Treated Firm Sample* is that of the BUs of the firm that are experiencing a tariff cut, the value for the control group is set to zero. No interaction is necessary.

DV: ΔResource Allocation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Competition Increases Patent Value				*Competition Decreases Patent Value*			
	Treated BU & Treated Firm		*Non-Treated BU & Treated Firm*		*Treated BU & Treated Firm*		*Non-Treated BU & Treated Firm*	
Tariff Cut	0.038 (0.317)	0.050 (0.232)	-0.045 (0.000)	-0.105 (0.000)	0.004 (0.832)	-0.009 (0.648)	-0.074 (0.013)	-0.104 (0.003)
Tech. Relatedness	0.006 (0.085)	-0.007 (0.017)	0.011 (0.042)	0.014 (0.048)	-0.008 (0.011)	-0.020 (0.007)	0.010 (0.319)	0.013 (0.374)
T. Cut X Tech. Rel.	-0.024 (0.034)	-0.025 (0.064)			0.003 (0.586)	0.006 (0.326)		
Year Fixed Effects	NO	YES	NO	YES	NO	YES	NO	YES
Control Variables	NO	YES	NO	YES	NO	YES	NO	YES
N. observations	432	432	746	746	344	344	454	454
Adj. R sq.	0.003	0.059	0.005	0.045	-0.007	-0.010	0.012	0.004

Note: Exact p-values in parentheses.

TABLE 1.4: Performance analysis

This table contains the results of regression analyses on the subsample of BUs of the *Treated BU & Treated Firm Sample* for which data is available for the calculation of the *Market-to-Book* and *Market-to Sales*. To keep the sample balanced if data was missing for one observation we also deleted the corresponding matched observation. The dependent variable is the difference in the average market multiples in the three years after minus the three years before the tariff cut. A description of the control variables and of the procedure for their calculation is available in the method section.

Dependent Variable	ΔMKT Book Model 1	ΔMKT Sales Model 2
Tariff Cut	0.105 (0.108)	0.093 (0.681)
ΔResource Allocation	-0.560 (0.000)	-1.596 (0.095)
T. Cut X ΔRes. Allocation	0.468 (0.000)	1.714 (0.077)
Year Fixed Effects	YES	YES
Control Variables	YES	YES
N. Observations	1372	1372
Adj. R sq.	0.048	0.056

CHAPTER II:

ENVIRONMENTAL CHALLENGES TO ORGANIZATIONAL AMBIDEXTERITY: THE EFFECT OF INTERNATIONAL COMPETITION

ABSTRACT

This paper uses a panel dataset of manufacturing U.S. firms to study how changes in international competition affect ambidexterity in organizations. Do firms respond to tougher international competition by searching for completely new solutions (exploration) or do they defend their position by improving current solutions (exploitation)? To obtain exogenous variation in international competition and estimate its causal effect on ambidexterity, we exploit changes in import penetration, which we instrument using exchange rates and scheduled tariffs. We find that tougher international competition causes an increase in technological exploitation and a decrease in technological exploration. Consistently, firms lower their investment in innovation activities and generate patents that are more incremental and therefore receive fewer citations. Our findings suggest that managers should take into account the extent of competitive pressure in the environment when designing an organizational structure to achieve ambidexterity.

Keywords: International Competition, Ambidexterity, Exploration, Exploitation.

CAPITULO II:

DESAFÍOS MEDIOAMBIENTALES PARA LA AMBIDEXTERIDAD ORGANIZATIVA: EL EFECTO DE LA COMPETENCIA INTERNACIONAL

RESUMEN

Esta investigación utiliza un conjunto de datos de empresas manufactureras estadounidenses para estudiar cómo cambios en la intensidad de la competencia internacional afectan la ambidexteridad organizativa. ¿Las empresas responden a una competencia internacional más dura buscando soluciones completamente nuevas (exploración) o defienden su posición mejorando las soluciones actuales (explotación)? Para obtener una variación exógena en la competencia internacional y estimar su efecto causal sobre ambidexteridad, explotamos los cambios en la penetración de las importaciones, que instrumentamos utilizando las tasas de cambio y los aranceles programados. Encontramos que una competencia internacional más dura causa un aumento en la explotación tecnológica y una disminución en la exploración tecnológica. Consistentemente, las empresas reducen su inversión en actividades de innovación y generan patentes que son más incrementales y, por lo tanto, reciben menos citas. Nuestros hallazgos sugieren que los gerentes deben tener en cuenta el grado de presión competitiva en el ambiente cuando diseñan una estructura organizacional para lograr la ambidexteridad.

Palabras clave: Competencia Internacional, Ambidexteridad Organizativa, Exploración, Explotación.

2.1 Introduction

The search for new knowledge and the refinement of existing technical skills are the two fundamental parts of the organizational adaptive systems that ensure a firm's short-term performance and long-term survival. A sizable literature has highlighted the benefits obtained by balancing the two activities (He and Wong, 2004; Katila and Ahuja, 2002; Tushman and O'Reilly, 1996).

Due to its nature, exploration is the vulnerable part of the equation that leads to organizational ambidexterity. Its higher risk, higher cost, and the longer time horizon of expected returns generate a tendency toward neglecting the activity in favor of exploitation (Levinthal and March, 1993; March, 1991). Both articles from the popular press (The Economist, 2007) and academic research (Arora, Belenzon, and Patacconi, 2017; Bhaskarabhatla and Hegde, 2014; Coombs and Georghiou, 2002) provide evidence indicative that this tendency is becoming stronger in recent years. For example, Arora and colleagues (2017) show that starting from the 1980s large corporations have consistently decreased their rate of investment in scientific research to focus on the development of commercial knowledge (i.e. patents). In a way, firms' engagement in basic research can be considered the purest form of exploration. Returns from developing scientific knowledge are typically very distant as the potential for commercial application of any discovery is unknown. Therefore, a decrease in the production of scientific research already constitutes a shift in the exploration-exploitation balance.

We contend that the trend exposed by Arora et al. (2017) is part of a change in the way firms approach innovation that it is not limited to basic research. Figure 2.1 contains a simple analysis of citations in patent applications over the period 1989-2006. Following Katila and Ahuja (2002), we classify a firm's use of a citation as exploitative if the firm has already used the same citation in patent applications made in previous years, vice-versa the citation is classified as explorative. The tendency that emerges is clear; firms are increasingly reusing familiar knowledge in the development of innovations.

***********************Please insert Figure 2.1 about here*************************

In this paper we focus on the increase in foreign competitive pressure as a factor that can possibly account for the observed shift toward exploitation. The increased exposure to international competition is probably the single most important environmental change faced by all firms in past fifty years (Krugman, Cooper, and Srinivasan, 1995). In the years between 1970 and 2015 the average worldwide ratio of imports to GDP more than doubled, passing from 13.5% to 28.7% (World Bank Data). Understanding how this trend affects a firm's ability to achieve ambidexterity is therefore relevant in order to give managers recommendations about a phenomenon with which they have to deal in their everyday activities.

Competitive environments have typically been associated with increases in the rate of failure, tighter profit margins, lower prices and a strong pressure toward efficiency (Matusik and Hill, 1998; Trefler, 2004; Zahra, 1996). We argue that there are two potential reasons for which environmental changes of the sort might lead firms to emphasize exploitation at the expenses of exploration. The first is an organization's tendency to react rigidly to the presence of threats in the environment (Staw, Sandelands, and Dutton, 1981). According to the threat rigidity hypothesis firms experiencing threats in their operating environment respond by reducing information processing, increasing the centralization of decision making, and increasing the attention to resource conservation (Audia and Greve 2006, Iyer and Miller 2008, Staw et al. 1981). Exploration instead constitutes the search for alternative solutions, which is fostered by decentralized decision-making (Jansen, Van Den Bosch, and Volberda, 2006) and by the availability of resources for experimentation (Nohria and Gulati, 1996). The second reason is that competition might incentivize opportunistic myopic behavior on the side of managers. Competition makes the performance target for the firm harder to achieve, and a failure to meet the targets generates career concerns on the side of managers (Easterwood and Nutt, 1999; Puffer and Weintrop, 1991). In such condition, extant theory and existing empirical evidence suggest that managers are incentivized to behave myopically (Graham, Harvey, and Rajgopal, 2005; Stein, 1988).

We investigate the relationship by forming a panel sample of U.S. manufacturing firms, which spans the years between 1991 and 2006. Following prior literature we use changes in import penetration to proxy for changes in the intensity of international competition experienced by U.S. firms (e.g. Bowen and Wiersema, 2005), and correct for potential endogeneity biases by using tariffs and exchange rates as instrumental variables (Cuñat and Guadalupe, 2009; Xu, 2012). We use five different dependent variables in our estimations to understand the broader picture of how international competition affects innovation strategies: R&D Expenses, Exploration, Exploitation, Patent

Applications, and the Number of Citations Received by the patents filed by the focal company

The results from the empirical analyses return a coherent story about the effect of international competition on exploration and exploitation. In our sample period an increase of 5 percentage points in import penetration, from 0.15 to 0.20, produces 9.4% decrease in the use of new citations in patent applications (exploration) and a 17.6% increase in the repeated usage of citations with which the organization is familiar (exploitation). Consistently, firms' investment in R&D decreases by 5.6% and the number of citations received by the patents for which firms apply decreases by 36.1%.

In separate analyses we further test whether we find support for Threat Rigidity and for Opportunistic Myopia as the two potential mechanisms influencing the relationship between competition and exploration. We find evidence for the first but not for the latter. Further our results also suggest that managers try to compensate for the decline in internal exploration by accessing external markets for technology (Arora, Fosfuri, and Gambardella, 2001).

We argue that our findings make a twofold contribution to extant literature. First, consistent with the trend exposed by Arora and colleagues (2017) we show that exploration is declining in corporate R&D, and we identify the increase in international competitive pressure as a key driver explaining this trend. Our additional analyses further suggest that the effect of international competition is at least partially due to a threat rigidity response, and that firms try to compensate for the decline in internal exploration by accessing external markets for technology.

Second, our findings make an important contribution to the organizational ambidexterity literature (He and Wong, 2004; Tushman and O’Reilly, 1996). While it is generally accepted that combining exploration and exploitation yield positive effects on firm performance (He and Wong, 2004; Katila and Ahuja, 2002), Cao and colleagues (2009) find that the balance dimension of ambidexterity (i.e. the close matching of exploration and exploitation in their relative magnitude) is especially beneficial for organizations operating in less munificent environments. In contrast, we find that in our context firms react to international competition by decreasing the level of investment in R&D, but instead of correspondingly decreasing patent production to maintain a balance between exploration and exploitation, they choose to do less of the former and more of the latter. We therefore submit that managers should be aware of the incentives provided by international competition when implementing architectural and contextual mechanisms aimed at achieving ambidexterity (Andriopoulos and Lewis, 2009; Fang, Lee, and Schilling, 2010; Gibson and Birkinshaw, 2004; Gupta, Smith, and Shalley, 2006).

2.2 Introducción

La búsqueda de nuevos conocimientos y el refinamiento de las habilidades técnicas existentes son las dos partes fundamentales de los sistemas de adaptación organizativa que aseguran el desempeño de corto plazo de una empresa y su supervivencia a largo plazo. Una considerable literatura ha destacado los beneficios obtenidos al equilibrar las dos actividades (He y Wong, 2004; Katila y Ahuja, 2002; Tushman y O'Reilly, 1996).

Debido a sus características, la exploración es la parte vulnerable de la ecuación que conduce a la ambidexteridad organizativa. Su mayor riesgo, mayor coste y el horizonte temporal más largo de los rendimientos esperados generan una tendencia a descuidar la actividad a favor de la explotación (Levinthal y March, 1993; March 1991). Tanto artículos en la prensa popular (The Economist, 2007) como trabajos académicos (Arora, Belenzon y Patacconi, 2017; Bhaskarabhatla y Hegde, 2014; Coombs y Georghiou, 2002) proporcionan evidencia indicativa de que esta tendencia se está fortaleciendo en los últimos años. Por ejemplo, Arora y sus colegas (2017) muestran que, a partir de la década de 1980, las grandes empresas han reducido constantemente su tasa de inversión en investigación científica para centrarse en el desarrollo de conocimiento comercial (es decir, patentes). En cierto modo, la participación de las empresas en la investigación básica puede considerarse la forma más pura de exploración. Los retornos de la inversión en conocimiento científico son típicamente muy distantes ya que se desconoce el potencial para la aplicación comercial de cualquier descubrimiento. Por lo tanto, una disminución en la producción de investigación científica ya constituye un cambio en el equilibrio exploración-explotación.

En este articulo sostenemos que la tendencia expuesta por Arora et al. (2017) es parte de un cambio en la forma en que las empresas enfrentan la innovación que no se limita a la investigación básica. La figura 2.1 contiene una simple análisis de las citas contenidas en las solicitudes de patentes durante el período 1989-2006. Siguiendo a Katila y Ahuja (2002), clasificamos el uso que una empresa hace de una cita como explotadora si la empresa ya ha utilizado la misma cita en solicitudes de patentes realizadas en años anteriores. Viceversa, la cita se clasifica como exploratoria. La tendencia que emerge es clara; las empresas reutilizan cada vez más su base de conocimiento consolidada en el desarrollo de innovaciones.

*********************** Por favor, inserte la Figura 2.1 aquí ******************

En este trabajo nos enfocamos en el aumento de la presión competitiva extranjera como factor que posiblemente pueda explicar el cambio observado hacia la explotación. La mayor exposición a la competencia internacional es probablemente el cambio ambiental más importante que han enfrentado todas las empresas en los últimos cincuenta años (Krugman, Cooper y Srinivasan, 1995). En los años comprendidos entre 1970 y 2015, la relación mundial promedio de importaciones al PIB aumentó más del doble, pasando del 13.5% al 28.7% (Datos del Banco Mundial). Comprender cómo esta tendencia afecta la capacidad de una empresa para lograr ambidexteridad es por lo tanto relevante para dar recomendaciones a los gerentes acerca de un fenómeno con el que deben lidiar en sus actividades cotidianas.

Los sectores altamente competitivos generalmente han sido asociados con tasas de fracaso mas altas, márgenes de ganancia más ajustados, precios más bajos y una fuerte presión hacia la eficiencia (Matusik y Hill, 1998; Trefler, 2004; Zahra, 1996). Argumentamos que hay dos posibles razones por las cuales incrementos en la intensidad competitiva podrían llevar a las empresas a enfatizar la explotación en vez que la exploración. La primera es la tendencia de una organización a reaccionar rígidamente ante la presencia de amenazas en su entorno (Staw, Sandelands y Dutton, 1981). Según la hipótesis de rigidez ante amenazas, las empresas que experimentan amenazas en su entorno operativo responden reduciendo el procesamiento de información, aumentando la centralización de la toma de decisiones y aumentando la atención a la conservación de recursos (Audia y Greve 2006, Iyer y Miller 2008, Staw et al., 1981). En cambio, la exploración constituye la búsqueda de soluciones alternativas, impulsadas por la toma de decisiones descentralizada (Jansen, Van Den Bosch y Volberda, 2006) y por la disponibilidad de recursos para la experimentación (Nohria y Gulati, 1996). La segunda razón es que la competencia podría incentivar un comportamiento miope y oportunista por parte de los gerentes. La competencia hace que el objetivo de rendimiento para la empresa sea más difícil de lograr, y el incumplimiento de los objetivos genera hace que el puesto de trabajo de los gerentes esté a riesgo (Easterwood y Nutt, 1999; Puffer y Weintrop, 1991). En tal condición, la teoría existente y la evidencia empírica sugieren que los gerentes están incentivados a comportarse de forma miope (Graham, Harvey y Rajgopal, 2005; Stein, 1988).

Investigamos la relación formando una muestra de empresas manufactureras de EE. UU., que comprende los años entre 1991 y 2006. Siguiendo la literatura anterior, utilizamos cambios en la penetración de las importaciones para representar cambios en la intensidad de la competencia internacional experimentada por las empresas estadounidenses (por ejemplo, Bowen y Wiersema, 2005). Además aliviamos posibles problemas de endogeneidad mediante el uso de aranceles y tasas de cambio como variables instrumentales (Cuñat y Guadalupe, 2009; Xu, 2012). Utilizamos cinco variables dependientes diferentes en nuestras estimaciones para comprender cómo la competencia internacional afecta las estrategias de innovación: Gastos de I + D, Exploración, Explotación, Solicitudes de Patentes y el Número de Citaciones Recibidas por las patentes presentadas por la empresa focal

Los resultados de los análisis empíricos arrojan una historia coherente sobre el efecto de la competencia internacional en la exploración y la explotación. En nuestro período de muestra, un aumento de 5 puntos porcentuales en la penetración de importaciones, de 0.15 a 0.20, produce una disminución del 9.4% en el uso de nuevas citas en solicitudes de patentes (exploración) y un aumento del 17.6% en el uso repetido de citas con las cuales la organización es familiar (explotación). Consistentemente, la inversión de las empresas en I + D disminuye de un 5,6% y el número de citas recibidas por las patentes para las cuales las empresas aplican disminuye en un 36,1%.

En análisis separados, evaluamos si encontramos apoyo para las hipótesis de Rigidez Antes Amenazas y Miopía Oportunista como los dos mecanismos potenciales que influyen en la relación entre competencia y exploración. Encontramos evidencia para el primero pero no para el segundo. Además, nuestros resultados también sugieren que los gerentes intentan compensar la disminución de la exploración interna accediendo a los mercados externos para la tecnología (Arora, Fosfuri y Gambardella, 2001).

Argumentamos que nuestros hallazgos hacen una doble contribución a la literatura existente. En primer lugar, en consonancia con la tendencia expuesta por Arora y sus colegas (2017), mostramos que la exploración está disminuyendo en la I + D corporativa, e identificamos el aumento de la presión competitiva internacional como un factor clave que explica esta tendencia.

Nuestros análisis adicionales sugieren además que el efecto de la competencia internacional se debe, al menos parcialmente, a una respuesta de rigidez frente a las amenazas, y que las empresas intentan compensar la disminución de la exploración interna accediendo a los mercados externos para obtener tecnología.

En segundo lugar, nuestros hallazgos hacen una contribución importante a la literatura de ambidexteridad organizacional (He y Wong, 2004, Tushman y O'Reilly, 1996). Aunque generalmente se acepta que la combinación de exploración y explotación produce efectos positivos en el rendimiento de la empresa (He y Wong, 2004; Katila y Ahuja, 2002), Cao y colegas (2009) encuentran que la dimensión equilibrio de ambidexteridad (es decir, la coincidencia cercana de la exploración y la explotación en su magnitud relativa) es especialmente beneficiosa para las organizaciones que operan en entornos menos favorables. En contraste, encontramos que en nuestro contexto las empresas reaccionan a la competencia internacional disminuyendo el nivel de inversión en I + D, pero en lugar de disminuir la producción de patentes para mantener un equilibrio entre la exploración y la explotación, eligen hacer menos de lo primero y más de el último. Por lo tanto, consideramos que es importante para los gerentes conocer los incentivos proporcionados por la competencia internacional al implementar mecanismos arquitectónicos y contextuales para lograr la ambidexteridad (Andriopoulos y Lewis, 2009; Fang, Lee y Schilling, 2010; Gibson y Birkinshaw, 2004; Gupta, Smith y Shalley, 2006).

2.3 Competition, exploration and exploitation

Exploration and exploitation are the two key components of organizational adaptive systems; long-term survival depends on the periodical acquisition of new knowledge and on the refinement of the knowledge acquired for its application in production processes. Too much focus on either of the two activities is problematic, as March (1991) puts it: *“Adaptive systems that engage in exploration to the exclusion of exploitation are likely to find that they suffer the costs of experimentation without gaining many of its benefits… Conversely, systems that engage in exploitation to the exclusion of exploration are likely to find themselves trapped in suboptimal stable equilibria”.* The empirical evidence supports this statement as its shows that balancing exploration and exploitation is leads to improved firm performance and long-term survival (Cao *et al.*, 2009; He and Wong, 2004; Hill and Birkinshaw, 2014; Katila and Ahuja, 2002).

The main challenge in achieving ambidexterity has usually been that of sustaining exploration in the face of a generalized organizational tendency to focus on exploitation (March, 1991). For example, Tushman and O’Reilly (1996) describe the struggle of semiconductor companies when faced with successive waves of disruptive innovation that substantially changed the technological paradigm of their industry. Their account of the industry evolution shows how incumbent firms were unable to prepare for the change in paradigm due the fear of losing their dominant position in legacy technology market. Levinthal and March (Levinthal and March, 1993) attribute this shortsightedness to the very characteristics of the learning process, which happens through simplification of experience and progressive specialization of responses. These same mechanisms in their view are responsible for different forms of myopia that, among other things, lead firms to focus on the short run at the expenses of long-term considerations.

We argue that an organization's tendency to focus on the short-term (and thus on exploitation) is likely to be enhanced in a context characterized by intense international competition. In the past decades, global markets have become increasingly interconnected due to factors like trade agreements (e.g. Trefler, 2004) and developments in information and communication technology (e.g. Freund and Weinhold, 2004). Consistently, the empirical evidence suggests that firms have substantially decreased their involvement in exploration by downsizing corporate labs and by diminishing their rate of contributions to basic science (Arora *et al.*, 2017; Bhaskarabhatla and Hegde, 2014; Coombs and Georghiou, 2002).

Competitive intensity refers to the degree of rivalry between the firms operating in an industry (Matusik and Hill, 1998; Porter, 1981). Competitive environments have typically been associated with tighter profit margins, lower prices and a strong pressure toward efficiency (Matusik and Hill, 1998; Zahra, 1996). Furthermore, international competitive shocks of the sort that substantially increase the exposure of domestic players to foreign competition, are associated with an increase in the rate of failure (Bernard, Jensen, and Schott, 2006; Trefler, 2004) and with a tendency toward worldwide industry consolidation (Helpman and Krugman, 1985).

There are two potential reasons for which increased international competition may lead firms to emphasize exploration at the expenses of exploitation. The first has to do with the expected reaction of individuals and organizations under threat; the second has to do with the fact that competition might incentivize opportunistic myopic behavior on the side of managers.

Threat Rigidity Theory (Staw *et al.*, 1981) postulates that organizations facing environmental threats, such as an increase in competitive pressure, will follow a predictable pattern of behavior. At the individual level, the response to environmental threats is linked to the psychology of stress, anxiety and arousal. Evidence shows that subjects experiencing these conditions exhibit an increased propensity toward emitting familiar, well-learned and habitual responses (Palermo, 1957; Zajonc, 1965), a reduction in information processing with a tendency to emphasize prior expectations (Eysenck *et al.*, 2007; Smock, 1955), and an increased (decreased) focus on the central (peripheral) cues in the environment (Eysenck, 1976; Wine, 1971). At the organizational level, the threat rigidity response results in a restriction in information processing, a constriction of control, and an increased attention toward the conservation of resources. All these tendencies are potentially linked to a decrease in firms' exploratory effort. Exploration requires organizations to consider alternative sources of knowledge. Instead, threats to security result in a restriction of the number of alternatives considered by strategy makers (Gladstein and Reilly, 1985; Smart and Vertinsky, 1977). Exploration is fostered in environments with relatively high decentralization of authority (Jansen *et al.*, 2006). By contrast Pfeffer and Leblebici (1973) found that firms operating in environments characterized by high degrees of competition exhibit a higher centralization in decision making. Exploration requires resources for experimentation (Nohria and Gulati, 1996). Instead, perceived threats are usually accompanied by tightening budgets and an increased attention toward efficiency (D'aveni, 1989; Irene Rubin, 1977).

Threat rigidity constitutes a natural response to a tougher competitive environment. Furthermore, competition also provides incentives for managers to engage in opportunistic behavior. A manager's performance is typically evaluated based on the performance of the firm to which he/she belongs. Evidence shows that market analysts fail to revise downwards the performance targets as a consequence of new negative information being released (Easterwood and Nutt, 1999). In turn, a firm's failure to meet the relevant performance targets results in large drops in the share price (Brown, 2001; Matsumoto, 2002; Skinner, 1994) and in significant concerns for a manager's career prospects (Puffer and Weintrop, 1991). Stein (1988, 1989) formally analyze the situation in which low current earnings cause the firm's stock to be undervalued and significantly increase the risk of takeover. He concludes that, under such contingencies, managers are incentivized to sacrifice the long-term interest of the firm to boost current profits. Campbell and Marino (1994) examine managers optimal self-interested behavior when they have control over an unobservable variable that affects the time distribution of returns on a firm's investment (the equivalent of controlling the choice between exploration and exploitation). They shows that when managers' ability is evaluated based on firm performance in a relatively short timeframe, and labor markets for managers are competitive and frictionless, then managers have an incentive to select myopic investments. In general, there is abundant evidence that shows how managers choose to sacrifice valuable investments opportunity in order to meet current profits target (e.g. Cohen et al. 2008, Cohen and Zarowin 2010, Graham et al. 2005, Roychowdhury 2006). For example, in a survey of 400 executives, Graham et al. (2005) report that 78% of the sample admits sacrificing long-term value to smooth earnings.

To conclude, we note that a change in balance between exploration and exploitation has implications for the entire innovation strategy of the firm. If international competition leads to more exploitation and less exploration, we also expect international competition to be associated with innovations that are less influential. Exploitative innovations in fact are, by definition, more likely to contain incremental knowledge and less likely to contain technological breakthrough. At the same time, innovations that exploit the current knowledge base of the firm are less costly to produce than innovations that require the acquisition of new knowledge. If international competition leads to more exploitation, we also expect international competition to either decrease R&D expenses or to increase the production of innovations. Due to lower unitary cost of exploitative innovations in fact, firms can maintain the production of innovations (patents) more or less at the same level while cutting the R&D budget. Alternatively, they can keep the R&D budget fixed and achieve a higher innovative output (sheer number of patents).

2.4 Empirics

The purpose of this paper is to investigate the effect of changes in the intensity of international competition on the balance between exploration and exploitation. To accomplish this aim we assemble a panel dataset of U.S. companies by combining data from different sources. We use the Standard & Poor's Compustat database to obtain information about firms' financials, firms' operating segments, and firms' expenditures in R&D activities. We use the NBER Patent Database (Hall, Jaffe, and Trajtenberg, 2001) to obtain information about firms' patent applications and about the citations made and received by firms' patents. We use data coming from different NBER datasets (Becker, Gray, and Marvakov, 2013; Feenstra, 1996; Feenstra, Romalis, and Schott, 2002; Schott, 2010) to calculate our measure of international competition: import penetration. Finally, we also use data on tariffs coming from the UNCTAD TRAINS dataset of the World Bank, and data on exchange rates and Consumer Price Indexes (CPIs) coming from the International Financial Statistics of the IMF for the calculation of our instrumental variables.

The resulting dataset effectively covers the period between 1991 and 2006 and it is limited to firms having their primary operations in manufacturing SICs (SIC 2000-3999), as trade information is available only for these sectors. The choice of the timespan is imposed by the limited availability of tariff data and patent data. The UNCTAD TRAINS database in fact starts in 1989 and we require two years of lagged observations for our analyses, while the NBER Patent Database ends in 2006. We eliminate from this data firms below 10 million dollars in sales. We use two samples for the analyses. The first sample contains all the firm-years for which there is information available in Compustat.

This sample has a total of 16,894 observations belonging to 2,193 different firms. The second sample instead is a subsample of the first and it contains the firm-years in which firms filed at least one patent application. The second sample has a total of 8,429 observations belonging to 1,317 different firms. The two samples will be used for testing the effect of international competition on separate aspects of the firms' innovation strategy. When discussing our dependent variables in the next session we will delve more deeply into the issue.

The general form of our regression models is the following:

$$\ln\left(Y_{f,t}\right) = \alpha_t + \gamma_f + \beta_1 ImportPen_{f,t-1} + \beta X'_{f,t} + \epsilon_{f,t}$$

Where $Y_{f,t}$ is one of our five dependent variables: R&D Expenses, Patent Applications, Citations Received, Exploitation, and Exploration, which we explain in detail below; α_t and γ_f are respectively year and firm fixed-effects; $ImportPen_{f,t-1}$ is our measure of import penetration lagged by one year; $X'_{f,t}$ is a vector of control variables, which depending on the regression includes the logarithm of sales, firm's ROA, R&D Expenses, Patent Applications, Patent Stock, and the total number of Citations Made by the patents for which the firm applied; $\epsilon_{f,t}$ is the error term. We cluster standard errors in all regressions at the firm level to allow for autocorrelation of the error term within firms and across years. Moreover, to reduce the influence of outliers we take the natural logarithm of all our dependent variables and controls except for ROA that we winsorize at the 1% level.

2.4.1 Dependent variables

We use five dependent variables in our analyses: R&D Expenses, Patent Applications, Citations Received, Exploitation, and Exploration.

Our proxy for a firm's investment in R&D is the natural logarithm of total R&D expenses coming from the Compustat Annual data file. The rest of our measures are calculated using data obtained from the NBER Patent-Assignee data file and the NBER citations data file.

Patent Applications is the total number of patents for which a firm applied in a given year and that were eventually granted. We account for whether a patent application is filed by multiple companies by dividing the weight of the patent equally between the owners.

Citation Received is the total number of citations received in the future by the patents filed by a firm in a given year. We correct for citation truncation due to the fact that the patent database ends in 2006 by multiplying the citations received by each patent for a correction factor estimated by Hall et al. (2001). The correction factor takes into account the technological field and the year of patent granting to estimate a grossing up factor that accounts for the citations received by a patent after 2006.

Consistent with prior research, we use the citation contained in patent applications to capture the constructs of technological Exploration and Exploitation (e.g. Choi, Kumar, and Zambuto, 2016; Sorensen and Stuart, 2000). In particular, we base ourselves on the seminal work of Katila and Ahuja (2002). Exploitation captures the extent to which the firm, in its patent applications, reuses a knowledge base with which is already familiar. We define the variable as the total number of times that citations in the focal year were repeatedly used in patent applications filed between t-1 and t-5. To avoid overinflating the measure we only count repeated usage of the same citation across the different years. As a result, each citation can take a value between zero and five depending on whether the citation has never been used in the five years prior to the focal year, or whether it has been used at least once in each of the five years prior to the focal year. Exploration instead captures the extent to which the firm searches for new knowledge to develop innovations. Consistently, the measure is defined as the total number of new citations contained in the patent applications. Again, a citation is defined as new if it was never used in patent applications filed by the firm between t-1 and t-5.

We transform all our dependent variables by taking the natural logarithm in order to reduce the influence of outliers on the estimates obtained from our regression models.

Note that we use separate measures to capture Exploration and Exploitation. While in general we agree with Lavie et al. (2010) in that single measures capturing the degree of exploration vs. exploitation are more appropriate in most cases (e.g. Lavie and Rosenkopf, 2006; Lin, Yang, and Demirkan, 2007; Uotila *et al.*, 2009), the use of separate measures in our study is justified by the fact that competition can induce firms to change their level of investment in R&D. An increase in R&D expenses would be consistent with increased levels of exploration but it wouldn’t necessarily imply decreased levels of exploitation. Firms could even increase their level of engagement in the two activities proportionally in order to maintain balance. A similar argument applies in the case in which firms decrease their investment in R&D.

2.4.2 Import penetration and instruments

Our identification strategy for international competition is based on the prior work of Cuñat and Guadalupe (2009) and Xu (2012). Consistently, our proxy for international competition is Import Penetration. We start by calculating the level of import penetration, for every year and for every four-digits manufacturing SIC (SICs 2000-3999), as the ratio between the value of imports divided by the total value of internal production plus imports. All the data necessary for this calculation comes from the NBER website. Data on imports were compiled by Feenstra (Feenstra, 1996), Feenstra, Romalis and Schott (Feenstra *et al.*, 2002), and Schott (2010), data on the value of shipments at the four-digits SIC level comes from the NBER-CES Manufacturing Industry Database (Becker *et al.*, 2013).

Import Penetration arguably is a good depiction of the extent to which foreign competitors are present in the U.S. domestic markets. Figure 2 shows that the trend over the sample period is generally upward. The average level of import penetration went from 13% in 1990, to 18% in 1998, to 25% in 2006. However, this tendency was not uniform across industries. As Figure 2.2 shows, some sectors start with a comparatively higher level of import penetration and experience a decline in the presence of foreign competitors while for other industries the trend is opposite. As a result, for every year in the sample period, our dataset contains a rich combination of changes in Import Penetration.

***********************Please insert Figure 2.2 about here*************************

For the purpose of our analysis, we refine our measure of import penetration by taking two further steps. First, we take the deviation in import penetration by subtracting the industry mean calculated between all sample years. This ensures that our measure does not capture unobserved differences across industries that are correlated with import penetration. Finally, we take into account whether the firm operates in different manufacturing industries by computing a weighted average (by segment sales) of the level of import penetration experienced by the firm in each of its industries. Taking into account whether the firm operates in multiple industries, instead of considering just the firm's main operating sector, ensures that our measure is a better reflection of the actual level of import penetration faced by the firm. However, it also presents further challenges, as the measure becomes dependent on endogenous production decision. To address this concern we keep the weights of the segments fixed and equal to the proportions of sales that the segments represent in 1998. For many firms the product offering changed radically in the years between 1990 and 2006, 1998 is halfway through the sample period and therefore it minimizes this problem. We have also repeated our analyses by changing the weight of the segments based on the proportion of total firm sales that the segments represent in each year. Results do not change.

Our empirical strategy fully exploits the panel nature of our datasets to include firm and year fixed-effects that control for unobserved heterogeneity.

Notwithstanding this advantage, results obtained from regressions on import penetration can still be subject to a number of criticisms in terms of endogeneity. For example, reverse causality issues may arise if changes in the level of exploration and exploitation of U.S. firms drive the behavior of foreign executives and therefore influence their presence in the U.S. market (e.g. Cornaggia *et al.*, 2015). Further, if firms anticipate changes in the level of imports the estimated effect will depend on the strategy adjustment that takes places after the intensity of international competition is manifest. Finally, our proxy for import penetration might be measured with error therefore causing attenuation bias. The presence of any of these problems would entail that the estimates obtained from our regression models are biased. To deal with these endogeneity concerns, we use current and lagged exchange rates as well as lagged tariffs to instrument for import penetration (Cuñat and Guadalupe, 2009; Xu, 2012).

We start by calculating measures of exchange rate and tariff at the sector level. Data on scheduled tariffs come from the World Bank UNCTAD TRAINS dataset and are available at the six-digits HS (Harmonized System) product level starting from 1989. Scheduled tariffs are superior in comparison to calculated average tariffs because they prevent the instrument from being mechanically correlated with imports.[10] From the TRAINS dataset we download data on the tariffs scheduled by the U.S. for each combination of trade partner and HS6 product category. Then, we use the NBER import data to calculate the

[10] Average tariffs are available through the NBER website. The problem with using average tariffs lies in the fact that these are calculated as the ratio between duties collected and value of imports, and the value of imports also enters in the calculation of the import penetration variable. As a result, any error in measuring imports would generate variation that mechanically improves the fit on the instrumented variable. Our goal is instead to isolate the variation due to changes in tariffs.

weight of each trade partner on the imports of every four-digits SIC in 1998, our baseline year. We keep this weight fixed, and we use it to compute a weighted average tariff for each combination of SIC4 and HS6 product category. To assign HS6 product categories to SIC4 industries we use a mapping developed by the US Census Bureau and available through the NBER website. Finally, we calculate the average scheduled tariff for each industry-year as the simple average of the tariffs calculated for all the products assigned to that industry.

Our proxy for exchange rate is also calculated at the four-digits SIC sector level. Following Bertrand (2004), we define the measure as the weighted average of the log real exchange rate of importing countries expressed in amount of foreign currency per dollar. We transform nominal exchange rates into real exchange rates using the trading partners Consumer Price Index (CPI). Data on CPIs and nominal exchange rates are obtained from the International Financial Statistics of the IMF. Again, we keep the weight of each trading partner constant throughout the sample period and equal to the share of imports that the country represents for each four-digits SIC in 1998. Following the procedure used for the calculation of our import penetration measure, exchange rates and tariffs are also demeaned and weighted to obtain firm-specific measure.

***********************Please insert Figure 2.3 about here*************************

For our instruments to be valid they have to be exogenous and satisfy the exclusion restriction. Being the dollar a freely floating currency, its exchange rate with other currencies is primarily determined by macroeconomic factors that affect its aggregate demand and supply. Examples are interest rates, inflation and the balance of payments between the U.S. and its trading partners. None of these factors is likely to be significantly affected by individual firm-level characteristics. Tariff rates instead are the result of international trade agreements and federal policy decisions and therefore are likely uncorrelated with firm-level innovation strategies. Nevertheless, one can still argue that executives might lobby to obtain increases in import tariff after experiencing an increase in competitive pressure. Figure 2.3 should mitigate this concern. The graph shows that the trend in tariff rate in the years of the sample period is consistently downwards. In particular, most of the decline in tariffs is concentrated in the years around 1995 when the results of the Uruguay round of the General Agreement on Tariffs and Trade (GATT) start being implemented. As an example between 1994 and 1995 the average tariff rate applied in the operating industries of the firms in our sample declined by 21%.

***************Please insert Tables 2.1, 2.2, 2.3 and 2.4 about here****************

2.5 Descriptive and Results

Table 2.1 contains the descriptive statistics. For each variable relevant for the analyses, we report both the raw value and the value of the transformation used in the regression models. As it is possible to see the distribution of many of the dependent variables is quite skewed, thereby justifying the use of logarithmic transformations. For example, the mean value for R&D Expenses in the full sample is 147 millions USD while the median is 11 millions USD. We mean-center Import Penetration and its instruments to prevent the variables from capturing cross-sector differences that are correlated with Import Penetration and that would prevent causal inference from our regression analyses. Furthermore, as described above, we use static segment weights to calculate Import Penetration for diversified firms. This helps in addressing the exclusion restriction since it increases the explanatory power of exchange rates and tariffs for imports and decreases the explanatory power for endogenous production decisions. The mean value of the raw import penetration measure is 0.2 over the sample period with a standard deviation of 0.14. For what concerns the average import tariff rate instead the mean value is 2.56 and the standard deviation is 2.46.

Table 2.2 reports the pairwise correlations. Many of the variables exhibit very high level of correlation but this is to be expected. For example, the total number of Patent Applications naturally is highly correlated with the total number of Citations Received (0.80), Exploitation (0.79), and Exploration (0.91). A high level of correlation in our case does not constitute a problem because potential multicollinearity issues only affect variables that will be used jointly as controls. For what concerns our independent variable, Import Penetration exhibits a highly negative correlation with tariffs (-0.61) and a low negative correlation with exchange rates (-0.07). The correlation of Import Penetration with Exploitation is positive and small (0.10), while the correlation of Import Penetration with Exploration is negative and small (-0.03).

Table 2.3 reports the results from first stage regressions for both the full sample and for the subsample of firm-years with a positive number of patent applications. The results are almost identical. In particular, columns 1 and 4 show that a real dollar appreciation significantly decreases Import Penetration in the same year while it significantly increases Import Penetration with a one-year lag. These results are consistent with the J-curve hypothesized in the literature of monetary economics (Bahmani-Oskooee and Ratha, 2004; Magee, 1973) and they are in line with the findings of recent studies (e.g. Cuñat and Guadalupe, 2009). Columns 2 and 5 instead replace exchange rates with tariffs and show that higher tariffs are associated with lower Import Penetration. Finally, columns 3 and 6 test the instruments jointly. The results show that the effect of both tariffs and exchange rates remains significant.

Conclusions about the validity of our instruments are further reinforced by the statistics reported in Table 2.4 together with the results from second stage regressions. We report statistics that are robust to violations of the i.i.d. assumption and that test for under-identification, weak identification, and for the over-identification restriction. The Kleibergen-Paap LM statistics test the null that the model is under-identified (i.e. the instruments are not correlated with the endogenous regressors). The null is rejected for all the models. The modified Kleibergen-Paap F statistics test for whether the model is identified but the instruments are only weakly correlated with the endogenous regressors. Weak instruments generate problems to the extent that they produce inconsistent instrumental variable estimators. Inconsistent estimators can be biased if the asymptotic distribution of the estimated parameters deviates substantially from the normal distribution (Stock, Wright, and Yogo, 2002). Stock and Yogo (2005) provide a table with the critical value of the F statistics for the weak instrument test at the 5 percent confidence level. In our case, the critical value is 13.5, while the Kleibergen-Paap F statistic of our models ranges between 84.6 and 48.7. Finally, we report the p-value from the Hansen-Sargan test of the over-identifying restriction (Hansen J). This is a test of the joint null that the excluded instruments are not correlated with the error term from the second stage regressions. The p-value associated with the Hansen J is never significant in any of the models. In particular, it ranges between from minimum of 0.45 in Model 4 to a maximum of 0.58 in Model 3. Therefore, the null cannot be rejected.

In our theoretical discussion we have argued that the increased exposure to foreign competitors is likely to be one of the determinants of the decline in Exploration observed by recent studies (Arora *et al.*, 2017; Bhaskarabhatla and Hegde, 2014; Coombs and Georghiou, 2002). International competition is in fact susceptible of generating both a threat rigidity response and incentives for opportunistic myopic behavior on the side of managers. Models 1 to 5 in Table 2.4 contain the results of our test. In particular, our dependent variables are five: R&D Expenses, Patent Applications, Citations Received, Exploitation, and Exploration. All regressions include firm and year fixed-effects and control for firm size and profitability. Depending on the specification, when necessary, we also control for R&D Expenses, number of Patent Applications, the size of the Patent Stock, and the number of Citations Made in the patent applications. We cluster standard errors by firm in all specifications to allow for autocorrelation of the error term within firm across years.

Model 1 tests the effect of Import Penetration on firms' expenditure in R&D activities. The effect is negative and significant (-1.11; p-value<0.05). Model 2 tests the effect of Import Penetration on the number of Patent Applications made by the firms. We find no effect. Model 3 tests the effect of Import Penetration on the number of Citations Received by the patents for which the firm applied. Here the effect is negative and highly significant (-7.24; p-value<0.01). Model 4 tests the effect of Import Penetration on Exploitation. The effect is positive and highly significant (3.53; p-value<0.01). Finally, Model 5 tests the effect of Import Penetration on Exploration. The effect is negative and highly significant (-1.88; p-value<0.01).

As it is possible to see, these results return quite a coherent picture supporting the idea that firms react to international competition by cutting exploration and increasing exploitation. Therefore, considering that the exploitation is relatively less costly, firms are able to save in terms of R&D expenses. However, while these savings do not affect the production of innovations in terms of number of patent applications, the innovations produced are less influential. In fact, international competition decreases the total number of citations received in the future by the patents for which the firm applies.

The magnitude of these effects is also highly significant. To put things into perspective, these coefficients imply that if Import Penetration increases by 5 percentage points, going for example from 0.15 to 0.20, this generates a 5.6% reduction of firms' investment in R&D, a 17.6% increase in exploitation, a 9.4% decrease in exploration, and in turn the citations received by the patents for which the firms apply decrease by 36.2%.

2.6 Complementary analyses

In the theory section, we outlined two possible mechanisms that could link an increase in international competition to a decrease in exploration. In this section, we engage in a series of complementary analyses with the aim of testing them. It is worthwhile noticing that the proposed explanations are not mutually exclusive.

***********************Please insert Table 2.5 about here*************************

The first mechanism conjectured the existence of a threat rigid response (Staw *et al.*, 1981) of incumbent domestic firms when faced with an increase in pressure from foreign competitors. Threat rigidity is the results of psychological and sociological mechanisms connected to the perception of existential threats in the firm's environment. It follows that organizational characteristics that influence the likelihood of failure should also influence the extent to which firms decrease their level of exploration as a result of international competition. Here we take into consideration two of these characteristics: The degree of product-market diversification and the extent to which the cost structure of the firm is fixed rather than variable. By lowering the variability of performance, product-market diversification is a well-known factor that decreases the likelihood of bankruptcy (e.g. Amit and Livnat, 1988). Therefore, we expect comparatively more diversified firms to reduce to a lesser extent their exploration efforts after an increase in international competition. Vice-versa the degree of operating leverage (the relative importance of fixed costs in the cost structure of the firm) influences the extent to which changes in sales affect firm profits. Firms with a higher degree of operating leverage are more likely to fail as a result of a decline in market share and therefore we expect them to engage in a comparatively higher reduction of exploration after an increase in competition. We measure Product-Market Diversification with the Entropy measure (Palepu, 1985). We measure Operating Leverage through the ratio between selling, general and administrative expenses over sales, consistent with research showing that this important cost item is relatively insensitive to declines in sales (Anderson, Banker, and Janakiraman, 2003). The results from the analyses are contained in Model 1 and 2 of Table 2.5 and support the idea that threat rigidity is at least partly responsible for the decline in exploration that follows an increase in international competition. The coefficient of the interaction between the Entropy measure of diversification and Import Penetration in fact is positive and significant in Model 1 (coeff. = 1.886; $p<0.05$), while the coefficient of the interaction between the Operating Leverage and Import Penetration is negative and significant in Model 2 (coeff. = -9.826; $p<0.01$)[11].

The second explanation that we have advanced deals with opportunistic myopic behavior on the side of managers. By increasing the difficulty of achieving the performance targets, international competition generates career concerns and incentives for foregoing valuable long-term investment opportunities. We test this explanation using both compensation and governance measures. If opportunism is responsible for the decline in exploration, we expect forward-looking incentive compensation to correct at

[11] For the sake of brevity, we report only the results of the tests on Exploration, nevertheless we also estimate the effect of these interactions on the rest of our proxies for innovation. In particular, the interaction between Diversification and Import Penetration is negative and significant on the number of Patent Applications and positive and significant on the number of Citations Received. The interaction between Operating Leverage and Import Penetration instead, is negative and significant on the number of Citations Received. These results are consistent with the main results on Exploration. They are available from the authors upon request.

least in part the problem. We take the logarithm of the total value of the unexercisable stock options held by the CEO as a measure of forward-looking incentive compensation. For what concerns our governance measure instead we use the Governance Index developed by Gompers et al. (2003), and available through Andrew Metrick website, to capture the extent a firm internal balance of power is tilted toward its management or toward its shareholders. We expect that the higher the level of the index and therefore the more the management is entrenched in the firm, the less the management will need to give up valuable long-term investment opportunities to boost current profits. The results from the analysis are reported in Model 3 and Model 4 in Table 2.5. Neither of the interactions between international competition and our measures of forward-looking compensation and governance is significant.

************************Please insert Figure 2.4 about here**************************

Figure 2.4 graphically depicts the effect of a 5 percentage point increase in import penetration for firms that are in the 25th, 50th, and 75th percentiles of Diversification and Operating Leverage. The values of the percentiles for the Entropy Measure of diversification are calculated only among diversified firms. As it is possible to see for both Diversification and Operating leverage the difference between the 25th and the 75th percentile of the distribution is of about 10%. Firms that are in the in the 75th percentile of the distribution for Diversification will do approximately 10% more exploration than firms in the 25th percentile of the distribution, the opposite occurs for Operating Leverage.

Finally, we investigate whether firms simply cut their investment in exploration or whether they try to substitute for its decline by finding cheaper sources of innovations. We expect the second option to be more likely as managers might find it easier to justify cutting internal R&D to stakeholders if there is a sizable supply of technology available to be either bought or licensed (Arora *et al.*, 2001). To test whether this is the case we follow Arora and Nandkumar (2012) and develop a measure of technological supply for each four-digits SIC sector by considering the one-year lagged stock of utility patents granted to universities and governmental agencies[12]. We expect that the higher the technology supply available for a sector the less firms will engage in exploration after an increase in competition because they can resort to market-based technology transactions. The result from the analysis is contained in Model 5 in Table 2.5. As it is possible to see, the empirical evidence is consistent with international competition leading firms to outsource the production of exploratory innovations. Indeed, the coefficient of the interaction between Technological Supply and Import Penetration is negative and significant on exploration (coeff = -0.461, p<0.05).

2.7 Discussion and Conclusions

[12] We use a five years rolling window in the calculation of the stock of patents. The procedure for the calculation of the measure involves four steps. First, we calculate the technological intensity of each sector by computing the total number of patents granted to the companies operating in that sector. Second, we calculate a “technological supply ratio” for every technological class by dividing the total number of patents granted to universities and governmental institutions by the total number of patents granted to firms. The technological supply ratio captures how many patents concerning a technology are potentially available for licensing for every patent that is owned by a firm. Third, we calculate the weight of each technology in what we call “technological mix” of each sector. The technological mix captures which technologies are used by the firms operating in an industry and in what proportion. We calculate the weight of technology “c” in the technological mix of industry “I” by dividing the total number of patents granted to firms operating in industry “I” concerning technology “c”, by the total number of patents granted to firms operating in industry “I”. Finally, we calculate our measure of supply of technology for an industry in the following way:

$$Tech.Supply_I = \sum_{c=1}^{N} Tech.Intensity_I \times Supply\ Ratio_{I,c} \times Weight\ in\ Tech.Mix_{I,c}$$

The underlying assumption is that university and governmental agency will tend to either license or sell the technology that they produce considering that they lack the downstream capabilities that are necessary for the commercialization.

This study addresses the effect of international competitive pressure on exploration and exploitation in the domain of technological innovation. Our results show how international competition produces an increase in technological exploitation and a decrease in technological exploration. To give an idea of the effect size, in our sample period an increase of 5 percentage points in Import Penetration produces a 17.6% increase in Exploitation and a 9.4% decrease in Exploration. Consistently, firms lower their investment in R&D by 5.6% and the number of Citations Received by the patents for which firms apply decreases by 36.1%.

We advance two theoretical mechanisms that might account for the observed relationship: Threat Rigidity and Opportunistic Myopia. According to Threat Rigidity (Staw *et al.*, 1981) organizations facing environmental threats, such as an increase in competitive pressure, will follow a predictable pattern of behavior that involves a restriction in information processing, a constriction of control, and an increased attention toward the conservation of resources. All these tendencies are potentially linked to a decrease in firms' exploratory effort. The Opportunistic Myopia explanation instead points toward managerial self-interest as the driver causing firms to forego valuable long-term investment opportunities in favor of investments with a shorter time horizon of expected returns. According to this account, competition increases the difficulty of achieving the firm's performance target (Easterwood and Nutt, 1999). This in turn threatens managerial employment security and provides incentive for opportunistic behavior (Campbell and Marino, 1994; Stein, 1988, 1989).

In separate analyses, we test each of the two theoretical mechanisms. We use firms' characteristics that affect the likelihood of failure as a result of competition (Product-Market Diversification and Operating Leverage) to test for Threat Rigidity. We use compensation and governance measure that influence the alignment of interests between managers and firms' shareholders (Value of Unexercisable Stock Options and the Governance Index) to test for Opportunistic Myopia. Our analyses provide support for Threat Rigidity but not for Opportunistic Myopia. We note however that the two mechanisms are not mutually exclusive and therefore they could potentially coexist. Further, our lack of support for the Opportunistic Myopia explanation might be partly due to the fact that the sample size of the analyses testing this mechanism is about half of that of the analyses testing for Threat Rigidity. Both our compensation and governance proxies in fact have a lot of missing values in our sample period.

We also provide evidence indicative that firms try to compensate for the decline in internal exploration by finding cheaper sources of innovation. The decline in exploration in fact is particularly strong in sectors in which there is a sizable supply of technology available to be either bought or licensed. We argue that this substitution is unlikely to lead to long-term competitive advantage, as external markets for technology are available to all sector incumbents. If these markets are at least to some extent efficient, then the rents generated by a valuable new technology will be appropriated by the seller. Furthermore, even if we assume that sector incumbents differ in their ability to identify valuable technology, firms that are not actively involved in exploration are unlikely to have an edge. The literature on absorptive capacity (Cohen and Levinthal,

1990) in fact teaches us that a firm's ability to recognize and exploit new technologies depends on the firm's experience with prior related knowledge.

Our findings make several contributions to the extant literature. First, our evidence is consistent with the results of academic studies that document the downsizing of large corporate R&D labs and the decline in the rate of firms' contribution to basic science (Arora *et al.*, 2017; Bhaskarabhatla and Hegde, 2014; Coombs and Georghiou, 2002). This literature suggests that firms are increasingly focusing on a narrower and more applied knowledge base; nevertheless these studies also show that firms' patenting activity (in terms of quantity) has either remained unaffected or has increased over time. We contribute to the debate by first showing that the nature of corporate patents has change over time in a way consistent with increasing technological specialization. Then, we identify the increase in international competition as a key driver responsible for this change in behavior. This finding also has implications for the debate on the relationship between competition and innovation (Aghion *et al.*, 2005; Bloom, Draca, and Van Reenen, 2016). While we are not concerned with the total amount of innovation produced in an economy, our findings do call for an increased attention to the quality of the innovation that is produced after an increase in competition. The relationship between competition and innovation quality (degree of exploitation and citations received) in our sample is negative.

Second, our results make an important contribution to the organizational ambidexterity literature (He and Wong, 2004; Katila and Ahuja, 2002; Tushman and O'Reilly, 1996). Recent findings in the literature suggest that balancing exploration and exploitation in their relative magnitude is particularly beneficial for firms that operate in environments characterized by low munificence (Cao *et al.*, 2009). In contrast, we find that in our context firms react to international competition by decreasing the level of investment in R&D, but instead of correspondingly decreasing patent production to maintain a balance between exploration and exploitation, they choose to do less of the former and more of the latter.

The only scenario in which this reaction is efficient is if prior to the increase in competition firms were in general doing more exploration than exploitation. While we have no means of testing for whether this is the case, we argue that this scenario is unlikely as adaptive systems naturally tend to overemphasize exploitation at the expenses of exploration (Levinthal and March, 1993; March, 1991; Miller, 2002). Therefore we submit that developing both architectural and contextual mechanisms for achieving ambidexterity is fundamental in a context characterized by intense competition (Fang *et al.*, 2010; Gibson and Birkinshaw, 2004; Gupta *et al.*, 2006).

On the methodological side the results obtained from our analyses are particularly robust. We test our hypotheses on a large panel dataset of U.S. manufacturing firms (SICs 20-39) that spans the period 1991-2006. The panel nature of the dataset allows for the inclusion of both firm and year fixed effects that control for unobserved heterogeneity at the firm level and unobserved trends. Further, we follow prior literature and instrument our independent variable, Import Penetration, using both exchange rate and tariffs (Cuñat and Guadalupe, 2009; Xu, 2012) to reduce endogeneity concerns and permit a causal interpretation of the results. Finally, to increase the confidence in the results, we estimate regressions also on other proxies for innovation such as R&D Expenses, the number of Patent Applications, and the number of Citations Received by the patents for which the firm applies. The results obtained from these analyses serve as a crosscheck for the consistency of the story about the effect of international competition on Exploration and Exploitation.

To conclude, we also acknowledge that our study suffers from some limitation. First of all, we test the effect of international competition on exploration and exploitation only in the domain of R&D. In recent years the literature has applied the concepts of exploration and exploitation to other functional domains such as marketing (e.g. Lavie, Kang, and Rosenkopf, 2011), and also to structural domains such as the formation of alliances (e.g. Lavie and Rosenkopf, 2006). There is no guarantee that the findings of this study will be generalizable to domains other than the one of technology. In explicitly acknowledging this limitation we join the call of other prominent scholars (Lavie *et al.*, 2010) and try to avoid the problems related to the overgeneralization of the findings that are plaguing the literature on exploration and exploitation. Second, our sample is composed entirely by U.S. firms. While we believe that our results should be generalizable to other national contexts we are not able to control for whether the idiosyncratic characteristics of the U.S. economy are influencing the relationship between competition, exploration and exploitation.

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FIGURE 2.1: PERCENTAGE OF EXPLORING AND EXPLOITING CITATIONS IN PATENTS (5-YEARS WINDOW)

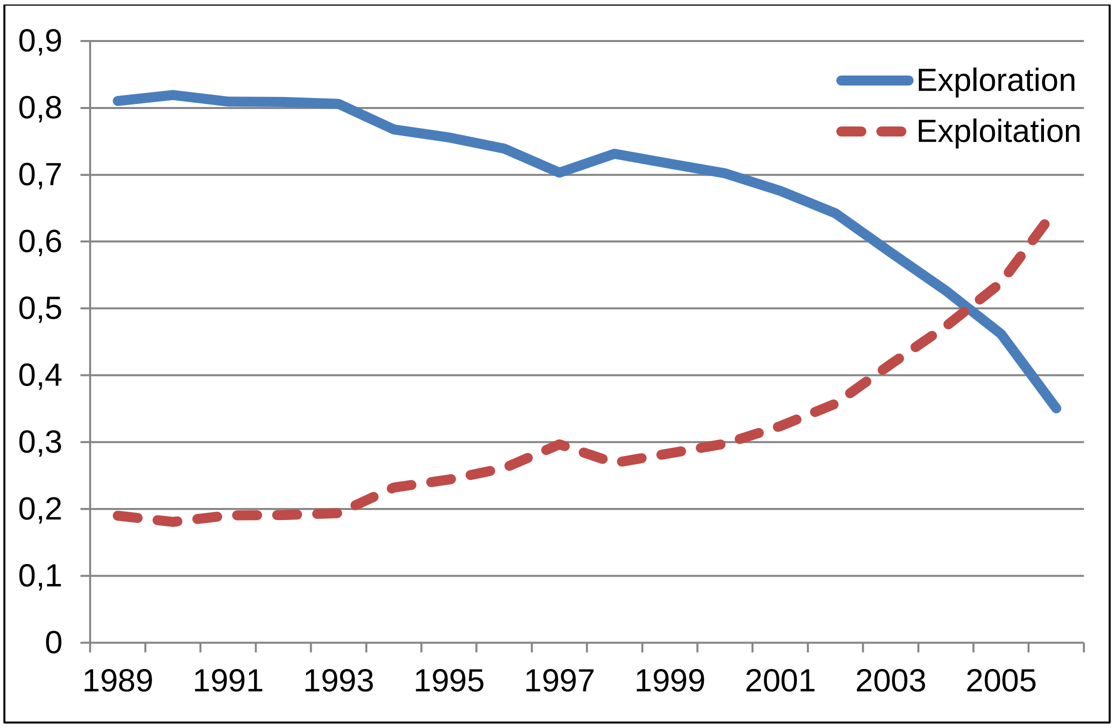


FIGURE 2.2: TREND IN IMPORT PENETRATION – AVERAGE AND BY SECTOR

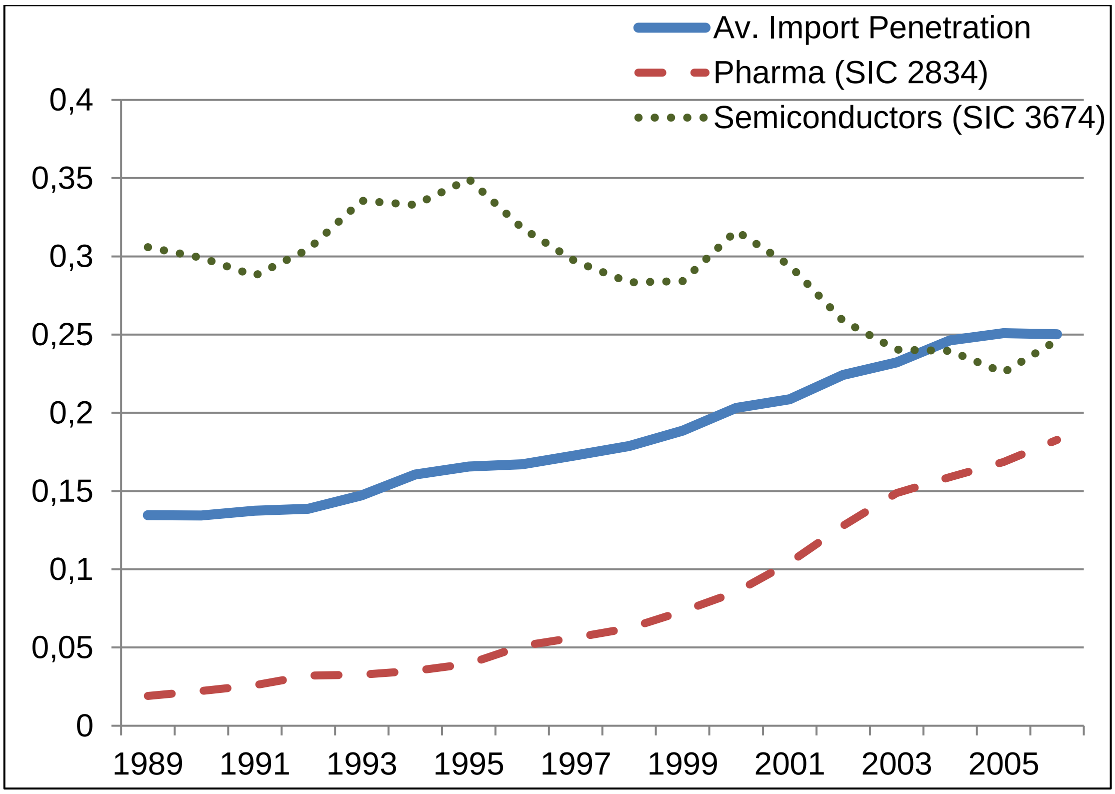


FIGURE 2.3: AVERAGE SCHEDULED TARIFF BY YEAR

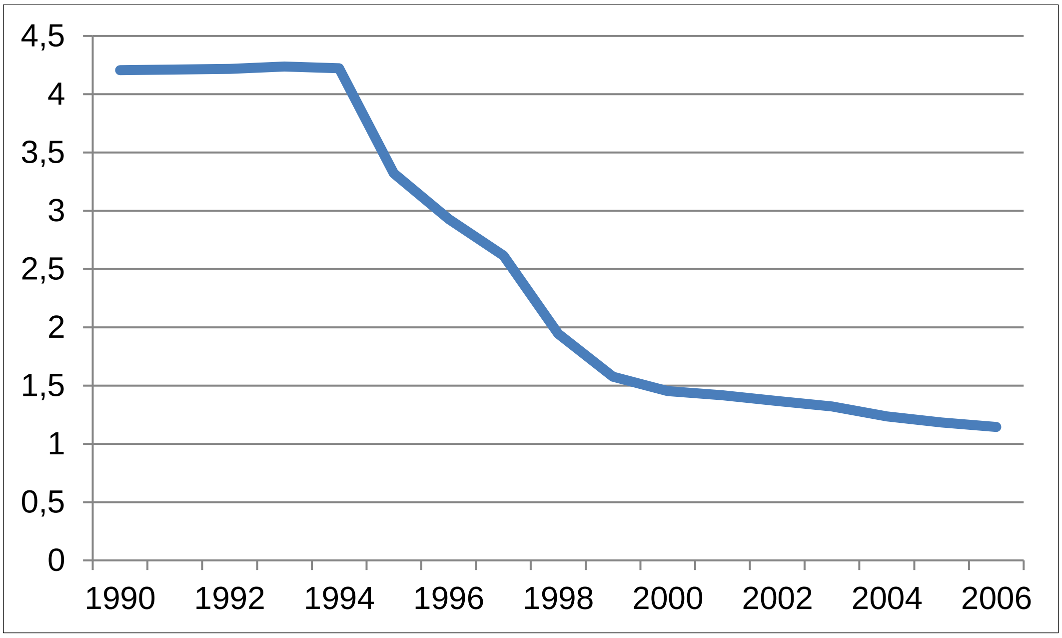
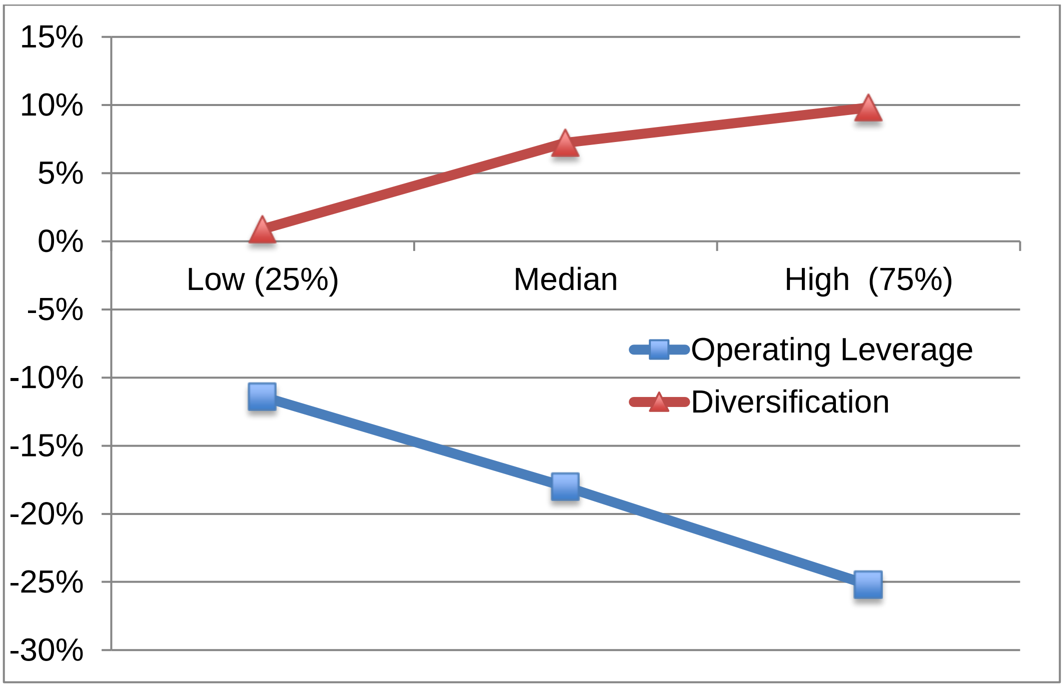


FIGURE 2.4: INTERACTION EFFECTS ON EXPLORATION FOR A 5 PERCENTAGE POINTS INCREASE IN IMPORT PENETRATION.



Note: The graph depicts the interaction effects of Diversification and Operating Leverage for a 5 percentage points increase in Import Penetration. For the Diversification interaction the value of the 25th, 50th and 75th percentiles are calculated only among diversified firms.

TABLE 2.1: DESCRIPTIVE STATISTICS

	Obs.	Mean	SD	p25	p50	p75
Dependent Variables						
R&D (raw)	16894	147.31	600.48	3.08	11.17	45.45
R&D (ln)	16894	2.81	1.84	1.41	2.50	3.84
Patents app. (raw)	16894	24.32	119.00	0	1.00	6.00
Patents app. (ln)	16894	1.17	1.57	0	0.69	1.95
Citations Received (raw)	8429	696.51	2703.56	12.30	59.07	266.32
Citations Received (ln)	8429	4.00	2.42	2.59	4.10	5.59
Exploiting Cit. (raw)	8429	560.36	3263.31	2.00	25.00	186.00
Exploiting Cit. (ln)	8429	3.34	2.55	1.10	3.26	5.23
Exploring Cit. (raw)	8429	301.92	948.47	13.00	43.00	169.00
Exploring Cit. (ln)	8429	3.95	1.82	2.64	3.78	5.14
Import Penetration & Instruments						
Import Penetration (raw)	16894	0.20	0.14	0.10	0.17	0.26
Import Penetration (mean c.)	16894	0.00	0.06	-0.03	-0.01	0.03
Exchange Rate (raw)	16894	2.53	0.73	2.06	2.53	3.05
Exchange Rate (mean c.)	16894	0.00	0.26	-0.13	0.03	0.15
Tariff Rate (raw)	16894	2.56	2.46	0.63	2.09	4.11
Tariff Rate (mean c.)	16894	0.07	1.48	-1.17	-0.03	1.19
Independent Variables & Controls						
Diversification	8429	0.20	0.36	0	0	0.36
Operating Leverage	7979	0.33	0.22	0.19	0.30	0.42
Unexercisable Stock Options (ln)	3705	5.28	3.58	0	6.37	8.10
Governance Index	3070	9.11	2.82	7	9	11
Technology Supply (ln)	8429	4.41	1.68	3.27	4.57	5.48
Sales (ln)	16894	5.57	2.05	3.97	5.19	6.81
ROA	16894	0.09	0.15	0.05	0.11	0.18
Citations Made (ln)	8429	4.38	1.88	3.00	4.20	5.64

TABLE 2.2: CORRELATIONS

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	R&D	1.00																
2	Patents App.	0.64	1.00															
3	Cit. Received	0.42	0.80	1.00														
4	Exploiting Cit.	0.57	0.79	0.58	1.00													
5	Exploring Cit.	0.62	0.91	0.78	0.70	1.00												
6	Self-Citations	0.62	0.88	0.67	0.89	0.79	1.00											
7	Imp. Penetration	0.09	-0.09	-0.28	0.10	-0.03	0.03	1.00										
8	Exchange Rate	-0.04	0.06	0.11	0.00	0.06	0.02	-0.09	1.00									
9	Tariff Rate	-0.11	0.06	0.30	-0.15	0.00	-0.07	-0.61	0.08	1.00								
10	Diversification	0.21	0.17	0.12	0.09	0.18	0.16	-0.01	0.02	0.00	1.00							
11	Op. Lev	0.01	-0.08	-0.11	0.00	-0.14	-0.08	0.09	-0.02	-0.14	-0.20	1.00						
12	Stock Opt.	0.25	0.18	0.11	0.17	0.14	0.17	0.03	-0.01	-0.05	-0.02	0.05	1.00					
13	Governance	0.09	0.06	0.01	0.06	0.06	0.09	0.01	-0.04	0.01	0.16	-0.12	0.02	1.00				
14	Tech. Supply	0.29	0.15	0.03	0.19	0.11	0.14	0.15	-0.08	-0.19	-0.12	0.32	0.16	-0.12	1.00			
15	Sales	0.80	0.54	0.38	0.46	0.57	0.54	0.05	-0.01	-0.05	0.35	-0.39	0.14	0.24	-0.01	1.00		
16	ROA	0.10	0.14	0.18	0.08	0.18	0.13	-0.07	0.00	0.14	0.07	-0.55	0.21	0.09	-0.13	0.34	1.00	
17	Citations Made	0.65	0.92	0.73	0.88	0.93	0.88	0.04	0.03	-0.08	0.14	-0.07	0.17	0.05	0.18	0.55	0.13	1.00

TABLE 2.3: FIRST STAGE REGRESSIONS

	Import Pen. (1)	Import Pen. (2)	Import Pen. (3)	Import Pen. (4)	Import Pen. (5)	Import Pen. (6)
	Full Sample			*Subsample with Pat. Applications*		
Exchange rate	-0.016**		-0.012**	-0.014**		-0.009*
	(0.000)		(0.000)	(0.002)		(0.040)
Lag Exch. Rate	0.028**		0.024**	0.020**		0.015**
	(0.000)		(0.000)	(0.000)		(0.000)
Lag Tariff		-0.014**	-0.014**		-0.014**	-0.014**
		(0.000)	(0.000)		(0.000)	(0.000)
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	16,894	16,894	16,894	8,429	8,429	8,429
R-squared	0.398	0.442	0.445	0.345	0.408	0.409

Note: The regressions of on the *Full Sample* include as controls Firm sales (log), Firm ROA, and R&D Expenses (log). Aside from these three control variables the regressions on the *Subsample with Patent Applications* include as controls the number of Patent Application in the year (log), The Patent Stock of the firm (log); and the total Number of Citations contained in the patent applications made by the firm in the year (log).
Note: P-values in parentheses. Two-tailed tests for all the variables in the models (+ p < .10; * p < .05; ** p < .01)

TABLE 2.4: SECOND STAGE

	R&D	Pat. Appl.	Cit. Received	Exploitation	Exploration
	(1)	(2)	(3)	(4)	(5)
Lag Import Penetration	-1.114*	0.225	-7.235**	3.528**	-1.883**
	(0.020)	(0.835)	(0.000)	(0.010)	(0.006)
Sales	0.750**	0.136**	-0.025	0.038	-0.031
	(0.000)	(0.000)	(0.628)	(0.492)	(0.300)
ROA	-1.241**	-0.266**	0.104	-0.179	0.142
	(0.000)	(0.002)	(0.495)	(0.314)	(0.175)
R&D		0.187**	-0.149**	-0.044	-0.001
		(0.000)	(0.001)	(0.361)	(0.981)
Patent Applications			1.288**	-0.053	0.460**
			(0.000)	(0.208)	(0.000)
Patent Stock				0.802**	-0.291**
				(0.000)	(0.000)
Citations Made				0.926**	0.693**
				(0.000)	(0.000)
Observations	16,894	16,894	8,429	8,429	8,429
KP LM	232.78**	234.32**	139.38**	141.60**	141.60**
KP F	84.585	84.859	48.744	49.749	49.749
Hansen J (p-v.)	0.454	0.460	0.584	0.447	0.508

Note: P-values in parentheses. Two-tailed tests for all the variables in the models (+ p < .10; * p < .05; ** p < .01)

TABLE 2.5: COMPLEMENTARY ANALYSES

Dependent Variable: Exploration	Model 1	Model 2	Model 3	Model 4	Model 5
Lag Import Penetration	-1.917** (0.005)	2.001 (0.130)	-1.387 (0.169)	0.776 (0.650)	0.322 (0.756)
Diversification X Imp. Pen.	1.886* (0.017)				
Op. Leverage X Imp. Pen.		-9.826** (0.001)			
Stock option X Imp. Pen.			-0.060 (0.587)		
Governance X Imp. Pen.				-0.155 (0.357)	
Tech Supply X Imp. Pen.					-0.461* (0.019)
Diversification	0.042 (0.194)				
Operating Leverage		-0.109 (0.397)			
Unexercisable Stock Options			0.004 (0.143)		
Governance Index				-0.002 (0.862)	
Technology Supply					-0.000 (0.993)
Controls	YES	YES	YES	YES	YES
Firm Fixed-Effects	YES	YES	YES	YES	YES
Year Fixed-Effects	YES	YES	YES	YES	YES
N	8,429	7,979	3,705	3,070	8,429
KP LM	141.156	130.685	63.371	58.238	134.947
KP F	26.266	19.858	12.587	9.526	22.618
Hansen J (p-value)	0.445	0.300	0.590	0.778	0.899

Note: All the regressions include as controls: Firm sales (log), Firm ROA, R&D Expenses (log), the number of Patent Application in the year (log), the Patent Stock of the firm (log), and the total Number of Citations contained in the patent applications made by the firm in the year (log).
P-values in parentheses. Two-tailed tests for all the variables in the models (+ p < .10; * p < .05; ** p < .01)

CHAPTER III

THE TECHNOLOGICAL ANOMALY: DOES THE MARKET UNDERSTAND TECHNOLOGICALLY RELATED DIVERSIFICATION?

ABSTRACT

This paper answers two related questions: (1) do diversified firms that operate in product markets that require similar technological inputs perform better than the rest of the conglomerates? (2) is the value creating potential associated with technological relatedness reflected in stock prices? We rely on patent data to develop two proxies that capture different aspects of a diversified firm's strategy in relationship with technology. Our results show that the performance of related diversifiers is superior to that of their peers but also that the market fails to fully impound the performance consequences of their strategy into the price of stocks. During our sample period an investment strategy focused on technology intensive firms that buys the stock of companies in the highest quartile for relatedness and sells the stock of companies in the lowest quartile for relatedness earns abnormal returns of around 8.8% per year.

Keywords: Related Diversification, Technology, Efficient Pricing.

CAPITULO III

LA ANOMALÍA TECNOLÓGICA: ¿EL MERCADO ENTIENDE LA DIVERSIFICACION RELACIONADA DESDE EL PUNTO DE VISTA DE LA TECNOLOGÍA?

RESUMEN

Esta investigación responde a dos preguntas relacionadas: (1) ¿Las empresas diversificadas que operan en mercados de productos que requieren tecnologías similares desempeñan mejor que el resto de las conglomeradas? (2) ¿el potencial de creación de valor asociado a la *related diversification* se refleja en los precios de las acciones? Usamos datos de patentes para desarrollar dos medidas que capturan diferentes aspectos de la estrategia de una empresa diversificada en relación a la tecnología. Nuestros resultados muestran que el rendimiento de los *related diversifiers* es superior al del resto de las diversificadas, pero también que el mercado no entiende y no incorpora por completo los beneficios de su estrategia en el precio de las acciones. Durante el nuestro período de muestra, una estrategia de inversión enfocada en empresas tecnológicamente intensivas que compra las acciones de empresas en el cuartil más alto por *relatedness* y vende acciones de compañías en el cuartil más bajo por *relatedness* obtiene retornos anormales de alrededor del 8.8% por año.

Palabras clave: Diversificación Relacionada, Tecnología, Precios Eficientes.

3.1 Introduction

Can corporate diversification create value? If so, can the market distinguish diversification strategies that create value from those that don't? These questions are as important as they are currently overlooked in the finance literature. In fact, the long-standing empirical and theoretical debate about the performance consequences of diversification has usually compared diversified firms with their focused counterparts, disregarding the nature of the diversification strategy. As a consequence, the literature on the topic is generally split between studies that find a negative relationship between diversification and performance (Berger and Ofek, 1995; Lamont and Polk, 2002; Lang and Stulz, 1994) and studies that question the validity of this finding (Campa and Kedia, 2002b; Graham, Lemmon, and Wolf, 2002; Villalonga, 2004).

The aim of this paper is to go beyond the dichotomy diversified vs. focused to start comparing diversified firms among each other. Our purpose is to identify those diversification strategies aimed at exploiting economies of scope in input utilization and see if the market is correctly pricing the stock of firms pursuing them. In particular, we focus on technological relatedness as a potential value creating mechanism. Extant economic theory suggest that due to the relatively low marginal cost of application, and high transaction cost, technology is one the firm's input of production that can constitute the basis for an efficient strategy of product diversification (Teece, 1980b, 1982). Moreover, focusing on technologically related diversification is also interesting because prior research has demonstrated that the market has difficulties in correctly impounding information about technology into the prices of stocks (Aboody and Lev, 2000; Cohen, Diether, and Malloy, 2013).

To answer our research questions, in section II of the paper we use the NBER patent database (Hall, Jaffe, and Trajtenberg, 2001) to built two measures capturing different and complementary aspects of level of technological relatedness among the business units of a diversified firm. The first measure, which we term Portfolio Relatedness, captures the average fit between a firm's patent portfolio and its operating sectors. The second measure, which we term Sector Relatedness, captures whether the operating sectors of the firm share a similar technological base.

Section 3.3 of the paper tests the two measures of measures of relatedness in a regression on accounting performance and market valuation multiples. We find that both measures of relatedness are positively associated with accounting performance. Their association with the market valuation multiples instead, is less stable and mostly not significant. Section 3.5 tests whether the positive association between relatedness and accounting performance found in section 3.6 translates into substantial return predictability. For this purpose, at the end of each calendar year, we assign the diversified firms in our sample to one of five portfolios of stocks based on the extent of their relatedness as calculated according to each of our relatedness measures. We find that the high relatedness portfolio is consistently associated with a positive alpha that is not explained by variance in well-known risk factors. Furthermore the alpha associated with each of the investments strategies based on our two measures of relatedness grows with the level of relatedness of the portfolio.

Section 3.7 investigates the relationship further. In particular we expect the significance of technological relatedness to grow with the level of technological intensity of the firm. Consistently we find that, between technology intensive firms, the portfolios of related diversifiers significantly outperform those of unrelated diversifiers. A long-short equity strategy aimed at exploiting these differences yields monthly alphas of around 700 basis points. Moreover, in section 3.6 we also explore the relationship between the abnormal alphas associated with related diversification, size and market discount. We find that the positive alpha associated with related diversification is mostly present in the group of firms with high levels of market capitalization. For what concerns the market discount instead, we find that the abnormal alpha is concentrated in the group of related diversifiers whose stock has been erroneously discounted by the market in the previous year.

Section 3.7 sets out three non-competing hypotheses to explain the results. Hypothesis 1 is that related diversifiers are followed by a relatively lower number of analysts and therefore forecasts about their stocks' performance are less accurate. Hypothesis 2 is that related diversification affects analysts' forecasting ability by increasing the chance of a positive earning surprise and decreasing the chance of a negative earning surprise. Hypothesis 3 is that the market does not recognize the value of unusual diversification strategies. We find support for both hypothesis 2 and hypothesis 3. In our logistics regression analyses both measure of relatedness are positively associated with positive earnings surprises and negatively associated with negative earnings surprises. Moreover, we find that the positive alpha is present only in that group of related diversifiers that are diversified between sectors that are mostly populated by single segment firms.

In section 3.8 we perform two additional robustness checks. First, we evaluate the persistence of the abnormal returns associated with related diversification over time. Second, we tests whether our results could be explained by two additional risk factors recently introduced in the literature (Fama and French, 2014). We find that the positive alpha associated with the related diversification is persistent across the time-span of the sample, even though it varies in significance. Moreover, we find that our results are qualitatively unchanged by the inclusion of a profitability and an investment factors. Section 3.9 concludes.

3.2 Introducción

¿Puede la diversificación corporativa crear valor? De ser así, ¿puede el mercado distinguir las estrategias de diversificación que crean valor de las que no lo crean? Estas preguntas son importantes y no tienen respuesta en la literatura financiera. De hecho, el debate empírico y teórico de larga data sobre las consecuencias de la diversificación en el desempeño usualmente ha comparado a las empresas diversificadas con sus contrapartes enfocadas, sin tener en cuenta la naturaleza de la estrategia de diversificación. Como consecuencia, la literatura sobre el tema generalmente se divide entre estudios que encuentran una relación negativa entre diversificación y desempeño (Berger y Ofek, 1995; Lamont y Polk, 2002; Lang y Stulz, 1994) y estudios que cuestionan la validez de este hallazgo (Campa y Kedia, 2002b; Graham, Lemmon y Wolf, 2002; Villalonga, 2004).

El objetivo de este estudio es ir más allá de la dicotomía empresa diversificada versus empresa enfocada para comenzar a comparar las empresas diversificadas entre ellas. Nuestro objetivo es identificar las empresas que persiguen estrategias de diversificación que tienen como objetivo explotar economías de alcance, y ver si el mercado está valorando correctamente sus acciones. En particular, nos enfocamos en la *technological relatedness* como un potencial mecanismo de creación de valor. La teoría económica existente sugiere que debido su coste marginal de aplicación relativamente bajo y a su alto coste de transacción, la tecnología es uno de los aportes de producción de la empresa que puede constituir la base para una estrategia eficiente de diversificación de producto (Teece, 1980b, 1982). Además, centrarse en la diversificación relacionada desde el punto de vista tecnológico también es interesante porque la investigación previa ha demostrado que el mercado tiene dificultades en valorar el efecto de la tecnología sobre el precio de las acciones (Aboody y Lev, 2000; Cohen, Diether y Malloy, 2013).

Para responder a nuestras preguntas de investigación, en la sección II del documento utilizamos la base de datos de patentes de NBER (Hall, Jaffe y Trajtenberg, 2001) para construir dos medidas que capturan aspectos diferentes y complementarios del nivel de relación tecnológica entre las unidades de negocios de una empresa diversificada . La primera medida, que llamamos *portfolio relatedness*, captura el ajuste promedio entre la cartera de patentes de una empresa y sus sectores operativos. La segunda medida, que denominamos *sector relatedness*, capta si los sectores operativos de la empresa comparten una base tecnológica similar.

La sección 3.4 del documento prueba las dos medidas de las medidas de *technological relatedness* en una regresión sobre el rendimiento contable y sobre múltiplos de valoración de mercado. Encontramos que ambas medidas de *relatedness* se asocian positivamente con el rendimiento contable. En cambio, su asociación con los múltiplos de valoración de mercado es menos estable y, en general, no significativa. La sección 3.5 comprueba si la asociación positiva entre la relación y el rendimiento contable que se encuentra en la sección 3.4 se traduce en una previsibilidad de los retornos de mercado. Para este propósito, al final de cada año calendario, asignamos las empresas diversificadas de nuestra muestra a una de cinco carteras de acciones en función de su grado de *relatedness* según lo calculado de acuerdo con cada una de nuestras medidas. Encontramos que la cartera de alta relación se asocia constantemente con un alfa positivo que no se explica por la varianza de factores de riesgo bien conocidos. Además, el alfa asociado con cada una de las estrategias de inversión basadas en nuestras dos medidas de *relatedness* crece con el nivel de relación de la cartera.

La sección 3.6 investiga la relación aún más. En particular, nos esperamos que la importancia de la *technological relatedness* crezca con el nivel de intensidad tecnológica de la empresa. Precisamente, encontramos que, entre las empresas intensivas en tecnología, las carteras de diversificadores relacionados superan significativamente a las de los diversificadores no relacionados. Una estrategia de cero inversión destinada a explotar estas diferencias produce alfas mensuales de alrededor de 700 puntos básicos. Además, en la sección 3.6 también exploramos la relación entre los alfas anormales asociados con la diversificación relacionada, el tamaño de la empresa y el descuento del mercado. Encontramos que el alfa positivo asociado con la diversificación relacionada está presente principalmente en el grupo de empresas con altos niveles de capitalización de mercado. Por lo que se refiere al descuento de mercado, encontramos que el alfa anormal se concentra en el grupo de diversificadores relacionados cuyo stock ha sido erróneamente descontado por el mercado en el año anterior.

La Sección 3.7 establece tres hipótesis para explicar los resultados. La hipótesis 1 es que los diversificadores relacionados son seguidos por un número relativamente inferior de analistas y, por lo tanto, las predicciones sobre el rendimiento de sus acciones son menos precisas. La Hipótesis 2 es que la diversificación relacionada afecta la capacidad de pronóstico de los analistas y aumenta las posibilidades de una sorpresa positiva o disminuye las posibilidades de una sorpresa negativa. La hipótesis 3 es que el mercado no reconoce el valor de las estrategias de diversificación inusuales. Encontramos apoyo tanto para la hipótesis 2 como para la hipótesis 3. En nuestra regresión logística, ambas medidas de *relatedness* se asocian positivamente con sorpresas positivas y negativamente con sorpresas negativas en los útiles de empresa. Además, encontramos que el alfa positivo está presente solo en ese grupo de diversificadores relacionados que están diversificados entre sectores que están mayoritariamente poblados por firmas de un solo segmento.

En la sección 3.8, realizamos dos pruebas de robustez adicionales. Primero, evaluamos la persistencia de los retornos anormales asociados con la diversificación relacionada a lo largo del tiempo. En segundo lugar, evaluamos si nuestros resultados podrían explicarse por dos factores de riesgo adicionales recientemente introducidos en la literatura (Fama y French, 2014). Encontramos que el alfa positivo asociado con la diversificación relacionada es persistente durante el lapso de tiempo de la muestra, a pesar de su variación de tamaño. Además, encontramos que nuestros resultados resisten a la inclusión de un factor rentabilidad y un factor inversión. La Sección 3.9 concluye.

3.3 Data and technological relatedness measures

All the data used in this study comes from three sources. We use the Standard & Poor's Compustat database to obtain firms' consolidated financial information and information about the operating segments. In particular, starting from 1976 companies are required by the Statement of Financial Accounting Standards (SFAS) No.14 (Financial reporting for segments of a business enterprise, 1976) to report relevant information about any industry segment that represents more than 10% of the total consolidated annual sales[13]. Information about monthly stock returns comes from CRSP. Patent data is obtained from

[13]Starting from 1998 SFAS No. 14 was superseded by SFAS No. 131 that introduced changes in the way segments are defined. Under SFAS No. 131, firms are required to report segments consistent with the internal organization of the business. Furthermore, the accounting items disclosed for each segment are defined consistent with internal segment information used to evaluate segment performance. The change introduced by SFAS No. 131 is significant, as SFAS No. 14 didn't specify any consistency requirement between the information used internally and that reported in the financial statements.

the National Bureau of Economic Research (NBER) patent database (Hall *et al.*, 2001).

We use the NBER patent data in conjunction with Compustat accounting data to develop two measures of relatedness that capture different aspects of the relationship between diversification strategy and technology. Details about the use of the databases in the calculation of the measures are available in Appendix A.

3.3.1 Patent portfolio relatedness

The first measure, Portfolio Relatedness (P-rel), captures the extent to which the technologies in a firm's patent portfolio are applicable across its operating industries. We follow Silverman (1999) for the calculation of the measure. For this purpose, we start by calculating the applicability of a technology to an industry as the share of innovations assigned to the same technological class that are manufactured and used in a given industry. We rely on the 2008 U.S. Patent and Trademark Office (USPTO) classification of utility patents (USPC) to categorize the various types of technologies contained in the patents. The USPTO classifies utility patents into about 470 main classes and 150.000 subclasses. Classes are designed to distinguish between technology types while subclasses differentiate between functional features and processes within a main technological class. For the development of our measure we categorize technology only using the main classes from the 2008 USPC. We assign patents to four-digits SIC sectors of usage by assuming that firms will use patents in their operating sectors. We use the SIC sectors reported in

Compustat to perform the assignment[14]. Finally, we account for the process of technological obsolescence by considering only patents granted within a five-years rolling window from the calculation of the measure. Technological applicability is therefore defined as:

$$A_{c,I,t} = \sum_{t-4}^{t} p_{c,I} \Bigg/ \sum_{t-4}^{t} p_c$$

Where $A_{c,I,t}$ is our measure of how applicable is the technological class "c" to the four-digits SIC sector "I" as calculated in year "t"; p_c is the total number of patents in technology class "c" granted in a given year; and $p_{c,I}$ is the total number of patents in technology class "c" granted in a given year that were assigned to companies operating in sector "I". For example, between 1991 and 1995 the USPTO granted 2041 patents in technology class 257 "Active Solid-State Devices". Of these, 673 where granted to firms operating in SIC 3674 "Semiconductors and Related Devices" and 208 to firms operating in SIC 3663 "Radio and Television Broadcasting and Communications Equipment". Therefore, as of 1995, the level of applicability of technology class 257 to SIC 3674 and SIC 3663, is of 0.33 and 0.1 respectively.

Knowing how applicable are technologies to sectors we calculate P-rel for each diversified firm in our sample by taking two further steps. First, we calculate the applicability of the firm's patent portfolio to an industry by performing a simple arithmetic average of the applicability of the firm's patents

[14] All the patents are equally weighted in the calculation of the measure of technological applicability. In the case of patents with multiple owners operating in different SIC codes we divide the total weight of the patent equally between the different SIC codes. In the case of patents owned by diversified firms we divide the weight of the patent between the different SIC codes by the proportion of segment sales.

to that industry. Second, we aggregate the measure at the corporate level by taking the average by segment sales of the applicability of the patent portfolio to the operating industries. Formally:

$$P - rel_{i,t} = \sum_{I} w_{i,I,t} * \sum_{c} A_{c,I,t} * \frac{p_{i,c,t}}{p_{i,t}}$$

Were $P - rel_{i,t}$ is the estimate of firm "i" portfolio relatedness in year "t"; $w_{i,I,t}$ is the percentage of sales that firm "i" has in sector "I" in year "t"; $p_{i,t}$ is the total number of patents in the portfolio of firm "i" in year "t"; and $p_{i,c,t}$ is the total number of patents in the portfolio of firm "i" in year "t" that are assigned to the technology class "c".

3.3.2 Sector technological relatedness

Our second measure of relatedness, Sector Relatedness (S-rel), is a sector cross-citation measure that ignores the technology owned by the single firm to focus on technological interactions at the industry level. The purpose of this measure is to capture the sharing of ideas across different industries. In fact, while P-rel captures the direct applicability of the patent portfolio to the operating sectors, S-rel captures the extent to which innovations developed for an industry can serve as the basis for subsequent innovations in related industries. Cross-citations measures have been widely used to capture the extent of inter-organizational knowledge flows (Mowery, Oxley, and Silverman, 1996; Schildt, Keil, and Maula, 2012). The calculation of our measure follows a similar logic to capture the potential for intra-organizational knowledge sharing between the units of a diversified firm. We consider cross-citations between a sector pair as a proxy for the extent to which the two sectors share a similar technological base. We argue that the more similar the technological base of two sectors, the more a firm will benefit by combining the two sectors within its portfolio of businesses.

We use the NBER patent citation data file to calculate S-rel and we attribute both cited and citing patents to SIC industries using the same procedure adopted for the calculation of P-rel. Next, we compute a five-years rolling sum of the total amount of cross-citation between each industry pair. The calculation is the following:

$$CrossCit_{A,B,t} = \sum_{t-4}^{t} C_{A\rightarrow B} + C_{B\rightarrow A}$$

Where $CrossCit_{A,B,t}$ is the total amount of cross-citation between the Sector A – Sector B pair as calculated in year "t"; $C_{A\rightarrow B}$ is the total number of times that patents granted in a given year to companies operating in the SIC sector A cite patents granted to companies operating in the SIC sector B; and $C_{B\rightarrow A}$ is the opposite.

Next, we calculate S-rel for each diversified firm in our sample by averaging the cross-citation between industries by the sum of segments sales. Formally:

$$S-rel_{i,t}=\sum_{X=1}^{N}\sum_{\substack{Y=1\\Y\neq X}}^{N} CrossCit_{X,Y,t} * \frac{s_{i,XY,t}}{\sum_{X=1}^{N}\sum_{\substack{Y=1\\Y\neq X}}^{N} s_{i,XY,t}}$$

Were $S-rel_{i,t}$ is the estimate of firm "i" sector relatedness in year "t"; "N" are the sectors in which a diversified firm is operating; and $s_{i,X,Y,t}$ is the sum of sales of operating segment "X" and operating segment "Y" for firm "i" in year "t".

The procedure for the calculation of S-rel present both advantages and disadvantages when compared with that of P-rel. On one side, by ignoring the technology owned by the firm, S-rel might prove less effective in capturing the extent to which a conglomerate company is a related diversifier. For the same reason however, S-rel allows us to relax one of the assumptions inherent in the calculation of P-rel. Namely, that a firm can benefit from operating in sectors that share the same technology only if it owns technology in the form of patents. We believe that relaxing this assumption can be a good choice for two main reasons. First, the procedure adopted by the NBER to match companies with patents is not perfect. There might be several cases of companies owning patents that have resulted in a non-match with patents in the database (Hall *et al.*, 2001). By calculating relatedness at the sector level we do not face this problem. Second and most important, not all the innovations are patented and therefore not having patents is not necessarily equal to not having technology. In fact, evidence suggests that companies seek patent protection only for a fraction of the most significant innovations (Fontana *et al.*, 2013).

3.3.3 Comments about the measures

Both P-rel and S-rel tend to be highly skewed, with a large share of diversified companies having a value of relatedness equal to zero. Graph 3.1 provide a graphic depiction of the reasons behind the skewedness of the measures. The graph represents the cumulative share of patenting activity for which the individual four-digits SIC industries were responsible in the period between 1996 and 2000. As we see, of the about 1000 different four-digits SIC industries, 5% are responsible for 80% of the patenting activity. In the case of P-rel this skewedness does not generate particular concerns for the analyses as the measure is bounded between 0 and 1. P-rel in fact is built on the ratio between the patents assigned to a sector that belong to a given technology class, and the total number of patents belonging to that technology class. S-rel instead is the total amount of cross-citation between a sector pair. The measure can therefore take very high values for firms combining sector pairs with strong technological linkages and in which patenting is a common protection mechanism for proprietary technology. This does not constitute a problem for the portfolios analyses, as it does not affect the division of stocks into quartiles of relatedness. For what concerns the performance regressions on the adjusted ROA and the adjusted market-multiples instead, we take the natural logarithm of the measure in order to avoid incurring in problems due to extreme observations.

Table 3.1 provides us with further information about the patenting activity over the same years. The upper section of the table lists the ten most patented technological classes together with their main sector of application. Not surprisingly, this group of technological classes has the highest share of its applicability in four sectors that are known for being technological intensive. In particular, the semiconductor and pharmaceutical sectors dominate the list followed by the photographic and broadcasting industries. The lower section of the table instead, lists the ten sector pairs with the highest amount of cross-citation. The strongest linkage that we find is between the photographic industry and the industry producing peripheral equipment for computers. This is probably due to the introduction of digital cameras over the same time span. Also in this case we see that the semiconductor industry appears repeatedly in the list, the pharmaceutical industry instead appears only once.

Table 3.2 lists in the upper section the ten conglomerates with the highest value of P-rel in the year 2000 and in the lower section the ten conglomerates with the highest value of S-rel. As we see the two groups do not coincide. This further confirms that the two measures capture different aspects of technological relatedness. In particular, firms operating in the pharmaceutical industry dominate the list for P-rel. The list for S-rel instead exhibits at the first place a well-known related diversifier like Canon. The company became famous already in the 1960s for its successful attempt of applying its photographic technology to the copy machine business. In the list for S-rel we also find five companies combining the SICs 3841 “Surgical and Medical Instruments and Apparatus” and 3845 “Electromedical and Electrotherapeutic Apparatus”. Both industries are technology intensive industries producing surgical and medical devices.

**************Please insert Graph 3.1, Table 3.1 and 3.2 about here***************

3.4 Technological relatedness and value creation

Can diversification create value? This question is as important as neglected in the finance literature. The analysis of diversification in the field in fact, has traditionally emphasized an agency theory perspective, both in the literature finding a diversification discount (Berger and Ofek, 1995; Denis, Denis, and Sarin, 1997; Denis, Denis, and Yost, 2002; Hoechle *et al.*, 2012; Laeven and Levine, 2007; Lang and Stulz, 1994; Rajan, Servaes, and Zingales, 2000), and in the literature questioning the diversification discount findings (Campa and Kedia, 2002a; Graham *et al.*, 2002; Villalonga, 2004).

In this paper we are concerned with the conditions under which diversification can be a value-creating strategy and therefore we need to analyze it through a different theoretical lens. In particular, following a transaction cost and resource-based logic (Penrose, 1959; Williamson, 1981), three conditions have to be met in order for firms to gain from diversification. First, a firm needs to have resources with unexploited capacity for which the marginal cost of application is substantially inferior to the cost of production. Second, there need to be profitable opportunities for exploiting this capacity in other markets. Third, the transaction cost of selling the extra capacity on the market has to exceed the cost of exploiting the resources within the hierarchical structure of the firm. Technology is the typical example of a resource respecting these three conditions. The cost of producing technology is normally higher than the cost of applying it. Basic technology has a number of applications in different product markets (Nelson, 1959; Scherer, 1965). The exchange of technology across organizational boundaries usually involves a high transaction cost (Teece, 1980a). These arguments lead to the prediction that firms that are diversified in industries with a similar knowledge base should create value compared to their industry peers (Teece, 1980a, 1982). Evidence on the topic is in general consistent with this prediction. Firms indeed seem to diversify based on the external opportunities for applying their technology (Silverman, 1999), and technologically related diversification has been shown to be positively correlated with performance (Miller, 2006).

In this section we test the effect of our relatedness proxies on measures of accounting and stock market performance. Based on the discussion above we predict and find a positive relationship between accounting performance and related diversification. Predicting the relationship between related diversification and market multiples is less straightforward. In order to find a positive relationship in fact, it is not sufficient for related diversification to create value, as the value creation process needs also to be visible to market participants. Investors however, as all human beings, are subject to attention constrains (Kahneman, 1973) and their ability to evaluate new information is limited. Empirical evidence suggests that information about technology is among the types of fundamental information not fully appreciated by investors (Chan, Lakonishok, and Sougiannis, 2001; Cohen *et al.*, 2013). Limited attention to information about technology would therefore be consistent with a capital market equilibrium in which the stocks of technologically related diversifiers are mispriced (Merton, 1987). Therefore, depending on whether investors recognize or not the benefits of technologically related diversification, we expect to find either a positive or a non-significant relationship with market multiples.

We test these hypotheses on a sample built by combining Compustat data and the NBER patent data files. The time span of the sample is between 1980 and 2006 as the NBER files cover the period 1976-2006, and as we use a five years rolling window for the calculation of the measures related diversification. We consider all the companies that are not matched with any patent to have zero patents. We adjust the sample by deleting 66.693 observations of the 151.185 firm-year observations with complete data available in Compustat between 1980 and 2006. Details about the adjustment procedure can be found in Appendix B. The final sample comprises 84.492 firm-year observations of which 22.060 are observations that belong to diversified firms.

The dependent variables that we use for the test are the adjusted ROA, the adjusted Market-to-Book and the adjusted Market-to-sales. The measures are adjusted to control for sector-level effects; the procedure for their adjustment is also described in Appendix B. We choose these ratios for the analysis in order to minimize the distortion due to accounting manipulation (Berger and Ofek, 1995). We estimate a separate set of regressions for each measure of related diversification. In particular the general form of our regression models is the following:

$$D'_{i,t} = a_t + b_1 Rel_{i,t} + \beta W_{i,t} + u_i + y_t + \varepsilon_{i,t}$$

where $D'_{i,t}$ represents the three industry-adjusted dependent variables, $Rel_{i,t}$ represents our relatedness measures P-rel and S-rel, $W_{i,t}$ is a vector of controls, u_i is the time invariant firm "i" fixed effect and y_t is a vector of year dummies. All regressions are estimated with standard errors clustered at the firm level. As elements of W we include proxies for size, leverage, competition, and technological intensity. For size we use either the natural logarithm of sales or that of assets. Leverage is calculated as the ratio of short and long-term debt over total assets. For competition we use the Herfindal Index of concentration defined at the 4-digit SIC sector level. We average the corresponding Herfindal Index of each segment by segment sale in order to calculate a single value for diversified firms. Finally, for technological intensity we use the five-year count of the number of patents granted to the firm.

Table 3.3 reports the descriptive statics for the final sample. The value of all the dependent variables is within the normal range of one standard deviation from zero. The value of P-rel, S-rel and the patent count appear to be skewed, with the mean value above the median for all the three variables. As we already saw in the section describing the measures, this is due to the fact that most of the patenting activity during the sample period is concentrated in few four-digits SIC sectors. The highest correlations in the table are between variables that proxy for the same construct, like sales and assets. In particular, the correlation between P-rel and S-rel is 0.48, while that of the two relatedness variables with the logarithm of the patent count is 0.53 both for P-rel and for S-rel.

Table 3.4 contains the result of regression analysis. Consistent with previous studies (e.g. Lang and Stulz, 1994; Rajan *et al.*, 2000) the diversification dummy is negative and significant on both market multiples (models 2 and 3). Interestingly, the five-year patents count that we use as a control variable is also negative and significant in many of the regressions. The literature provides some evidence that technological intensity could be a priced risk factor (Chan *et al.*, 2001; Hsu, 2009). If this is the case, than the negative correlation between the patent count and the market multiples could be interpreted as evidence that investors require higher returns from technology intensive firms. A thorough investigation of the reasons behind this negative coefficient is however beyond the scope of this paper.

Models 1 and 4 test the effect of related diversification on the industry-adjusted ROA. The coefficients provide support for the hypothesis that related diversification increases accounting performance, both in the test with P-rel (t = 3.46) and in the test with S-rel (t = 1.92). Models 2 and 5 test the effect of related diversification on the industry-adjusted Market-to-Book value. In this case the test with P-rel returns positive and significant coefficients for related diversification (t = 2.40) while the test with S-rel returns a non-significant coefficient. The rest of the models test the effect of related diversification on the industry-adjusted Market-to-Sales. None of the tests provide significant results in this case. Overall, the results are consistent with the idea that related diversification is a value-creating factor. However, the results that we have obtained in the test market multiples are not enough to understand whether the market fully recognizes it as such. In the next section we test the effect of related diversification on returns. Only evidence that related diversification is associated with substantial return predictability can justify the conclusion that the benefits of related diversification are not fully appreciated by the market.

*******************Please insert Table 3.3 and 3.4 about here********************

3.5 Technological relatedness and returns

In this section we test whether the market understands and immediately incorporates in the stock price the performance consequences of technologically related diversification. If this is the case, any investment strategy built to exploit the fact that related diversifiers obtain a superior performance in comparison to that of the rest of conglomerates should not provide returns in excess of those obtainable by investing in other known risk factors. If instead the market does not immediately incorporate the information about related diversification this should result in substantial return predictability. In the literature there are plenty of examples of investor's biased or delayed reactions to firm-specific public information (e.g. Hirschey and Richardson, 2003; Sloan, 1996; Zhang, 2006). We contribute to this stream of research by showing that portfolios of firms that are related diversifiers historically yielded a positive and statistically significant annual return that ranged between 4.83 and 2.61 percent, which is not accounted for by other well-known risk factors.

In order to perform the test we form a sample of diversified firms by merging the CRSP monthly data file with our database containing the measures of relatedness. We match the monthly returns associated with a security in year t with the estimates of P-rel and S-rel calculated for the year t-1 to avoid incurring in a look-ahead bias. Finally we eliminate all the observations with missing monthly returns or with monthly returns calculated on the bid-ask spread average instead of on actual transactions. Our final sample comprises 336.859 monthly returns associated with 4.538 different securities covering the period between 1981 and 2007.

We use a standard portfolio methodology (e.g. Cohen and Lou, 2012) to form five portfolios, based on either P-rel or S-rel, which are recalculated at the 31st of December of each year. Given that both our relatedness variables are highly skewed we first assign all the observations for which the value of the relatedness measure is equal to zero to a zero portfolio, then we divide the rest of the sample into quartiles based on the distribution of either variable in a given year. For example the portfolios of P-rel to which the returns from 1995 are assigned are based on the distribution of P-rel in our sample of firms in the year 1994. For each portfolio we calculate both an equal weighted and a value weighted monthly return. The equal weighted monthly return is a simple average of the returns associated with each portfolio. The value weighted monthly return instead is calculated based on the market capitalization exhibited by a security at the 31st of December of year t-1 relative to the rest of the firms in the portfolio.

Table 3.5 reports some descriptive statistics about the portfolios formed on either of the variables. The statistics are calculated as the average between all the 324 months in the sample. As is possible to see, given that P-rel is calculated on the actual patents stock of a company, its distribution is more skewed than that of S-rel with a much higher number of companies being assigned to the zero portfolio. Both variables are associated with size and the number of patents; in particular the firms assigned to the highest portfolio of both measures of relatedness have on average about six time the market capitalization of firms assigned to the zero portfolio. Given that size has been shown to have a significantly negative correlation with returns we could expect the highest portfolios to have decreasing average returns. This does not seem to be the case; the highest portfolios of technologically related diversification exhibit an average return that is in line and at times higher than the rest of the portfolios.

***********************Please insert Table 3.5 about here**************************

We cannot however draw any conclusion about the effect of related diversification on returns simply by looking at average return of each portfolio. The portfolios of related diversification that we have formed might in fact differ between them based on some other factor that we are currently not observing. In order to take into account the most important characteristics of securities that have been found to be associated with returns we estimate the Carhart (1997) four-factor model as a method of performance attribution. The returns of a diversified portfolio have in fact been demonstrated to be particularly sensitive to four factors that alone are able to explain most of the variance in average returns. Apart from the market risk premium deriving for the CAPM, the market capitalization of a stock, the book-to-market ratio and a stock's past returns have all been showed to hold significant explanatory power in explaining the cross-section of returns. Hence, in order to test our hypothesis we specify the following model:

$$(5)\ R_t = \alpha + \beta_1 * RMRF_t + \beta_2 * SmB_{\ t} + \beta_3 * HmL_t + \beta_4 * Mom_t + \epsilon_t$$

where R_t is the monthly return of the portfolio in excess of the one month T-bill, $RMRF_t$ is the excess return associated with the market portfolio calculated in the same way, and $SmB_{\ t}$ (Small minus Big), HmL_t (High minus Low) and Mom_t (Momentum) are the month t returns associated with zero-investment portfolios designed to capture the sensitivity of stock returns to size, book-to-market and past returns. The alpha of the model represent the abnormal monthly return that is possible to realize by investing in the portfolio once we account for the other factors. If the Carhart model fully manages to explain the return premium of the portfolio and all of what is left is random noise, the alpha should then not be significantly different from zero. If instead our trading strategy based on relatedness proves effective we expect to find a significantly positive alpha for the companies included in the highest portfolios of related diversification. We take no position about what should be the expected alpha sign and significance for the portfolios containing the companies with the lowest values of technologically related diversification. While we expect technologically unrelated diversification to increase the complexity a firm's internal operations and therefore its coordination cost, the market already places a discount on the stock of diversified firms (Berger and Ofek, 1995). Depending on whether the market has underestimated the costs deriving from technologically unrelated diversification the alpha of the portfolio of unrelated diversifiers might either be negative or non-significant.

Table 3.6 contains the results of the estimation of (5) for each of the five portfolios formed on either P-rel or S-rel, for both value weighted and equal weighted returns. The coefficients associated with our factor controls are consistent with prior work (e.g. Cohen and Lou, 2012). The market risk premium is associated with higher returns for all portfolios as expected. The size factor is negative and significant for high relatedness portfolios meaning that these portfolios tend to incorporate firms of bigger size. The value factor also tends to be negative for firms in the high relatedness portfolios meaning that the firms in these portfolios are perceived as having lower growth opportunities. Finally the momentum factor is negative and significant for the firms in all portfolios.

For what concerns the main results, as predicted the alpha is positive and significant in all the portfolios formed using the highest quartile of related diversification. In the case of value-weighted returns the alpha of the highest relatedness portfolio is the only positive and significant coefficient for both P-rel (coeff. = 0.291, t = 2.58) and S-rel (coeff. = 0.215, t = 2.28). Furthermore, the alpha of the highest relatedness portfolio corresponds to excess return in the order of 355 and 261 bps annually. In the case of equal-weighted returns instead, while there are other positive and significant coefficients, the α of the last portfolio is the highest and the most significant (coeff. = 0.394, t = 3.84 for P-rel; coeff. = 0.380, t = 3.52 for S-rel). In this case the excess return is even higher corresponding to 483 and 366 bps respectively. Moreover, the alpha seems to increase with the relatedness of the portfolio for both P-rel and S-rel.

************************Please insert Table 3.6 about here**************************

3.6. Exploring the relatedness anomaly

3.6.1 Technological relatedness and technological intensity

In this section we test whether the positive effect of relatedness on returns is stronger for technology intensive firms. We expect the gains of operating in technologically related sectors to increase together with the technological intensity of the firm; likewise for the cost of operating in technologically unrelated sectors. We use the five-years patent count as a measure of a firm's technological intensity and we form portfolios based on it. In particular, we define technology intensive firms as those firms whose size of the patent portfolio is above the median value for that year[15].

To form the portfolios we divide the sample of technology intensive firms in four groups using cutoffs determined as the quartiles of the yearly distribution of each related diversification measure. The division into portfolios for either measure is done at the 31st of December of each year prior to that of the returns. The dependent variable is the monthly value-weighted risk premium of the portfolio (value-weighted return of the portfolio minus the return form the one month T-bill). The value weighting of returns is done based on the market

[15] Through this approach we also control for whether our results about relatedness are due to a general mispricing of innovation (Cohen *et al.*, 2013). In this latter case the positive and significant alfa would be present in all portfolios of technology intensive diversified firms.

capitalization of a stock in comparison with that of the rest of the stocks falling in the same portfolio. The market capitalization is that exhibited at 31st of December of the year prior to that of the return.

Table 3.7 contains the results of the estimation of (5) for the four portfolios of technology intensive firms formed using the strategy described above. The results show that the effect of technological relatedness is substantially stronger for companies with a high degree of technological intensity. The alpha of the high relatedness portfolio calculated on the subsample of technology intensive firms in fact, is higher that that of that that associated with the high relatedness portfolio calculated on all firms (coeff = 0.346, t = 2.44 for P-Rel; coeff = 0.378, t = 3.27 for S-Rel). Moreover, the alpha coefficient of the portfolios in Table 3.7 grows with relatedness in an almost linear fashion. The last two rows of the table for each relatedness measure contain the results for the zero-investment portfolio (4-1) that takes a long position on technology intensive related diversifiers and a short position on technology intensive unrelated diversifiers. Over the timespan of our sample this strategy earned annual abnormal returns of 8.5 percent in the case of P-Rel (coeff = 0.684, t = 3.03) and of 8.8 percent in the case of S-Rel (coeff = 0.707, t = 2.88).

***********************Please insert Table 3.7 about here*************************

3.6.2 Technological relatedness and market capitalization

One common problem when using sorts of an anomaly variable to judge its effect on returns is that micro stocks tend to be overrepresented in the extreme portfolios (Fama and French, 2008). This raises the possibility that the positive and significant alpha that we find in our high relatedness portfolio might be attributed to the fact that these stock are typically illiquid and command a higher risk premium. Using value-weighted returns only accounts for part of the problem given that if all the stocks in a portfolio are micro stocks than the value weighting of the returns will be done only between them. We expect the chances of the effect being due only to micro stocks to be slim given that already in table 3.5 we saw that the market capitalization of a stock tend to grow together with the value of our relatedness variables. In any case, in order to exclude the possibility, we adopt Fama and French (2008) procedure and we divide the stocks in our sample in three groups of micro, small and big stocks based on two cutoffs defined as the 20th and 50th percentile of market capitalization of the NYSE at the 31st of December of the year of portfolio formation. We combine the three size groups with the same five groups based on related diversification that we formed for the analysis contained in table 3.5, this leads to a total of fifteen portfolios for both P-rel and S-rel.

The results of the estimation are contained in table 3.8. The effect related diversification on returns in the portfolios built using P-rel appears not to be due to microcaps. The alpha coefficients of the high-relatedness portfolio are positive and significant for both small stocks (coeff. = 0.641, t = 3.24) and big stocks (coeff. = 0.300, t = 2.67), while the alpha of the other relatedness portfolios built using small and big stocks are not significant and in general seem to grow together with the relatedness variable. For what concerns micro stocks the relationship between returns and relatedness appears to be quite random. The alphas are always positive and the only significant ones are those of portfolio number one and portfolio number two.

For what concerns the test using S-rel instead, part of the effect of relatedness of return seem to be due to micro stocks given that the alpha of the high relatedness portfolio in the micro stock group is positive and significant (coeff. = 0.584, t = 2.55). However, this is also the case for the alpha of the high relatedness group built using only big stocks meaning that the effect is present also in this size group (coeff. = 0.233, t = 2.42). Moreover, also in the case of S-rel with the exception of portfolio number one, both the small and the big size group display alpha coefficients that grow together with the relatedness variable.

Generally speaking we believe that there is sufficient evidence to show that the effect of relatedness is not exclusively due to the presence of micro stocks in the portfolios.

***********************Please insert Table 3.8 about here*************************

3.6.3 Technological relatedness and industry performance

We have found evidence that related diversifiers perform better than other diversifiers and that they obtain in the long run higher returns. The following analysis is concerned with the timing of the abnormal return. Extant evidence indicates that market participants find it difficult to incorporate the consequences of positive and negative sector-level information into the stock price of diversified firms. This at times causes the update to happen with a delay (Cohen and Lou, 2012). If the same dynamic is at play also in the evaluation of the stock of related diversifiers, than we expect that related diversifiers that have underperformed in comparison to the norm of their operating sectors will subsequently earn higher abnormal returns.

To conduct this test we follow the methodology of Cohen and Lou (2012) and we calculate for every conglomerate company in the sample a “would be” normal market return due to the participation in its industries. We assume the normal return from the participation in an industry to be that yield in a predefined time period by a value-weighted portfolio of single-segment firms participating solely in that industry. For every year between 1981 and 2006 we create portfolios of single segment firms based on their reported four-digits SIC code. We then value-weight the return of every stock based on the market capitalization exhibited at December 31st of the year prior to that of the return. Finally, we compute the normal return for a conglomerate firm as the average by segment sales of the normal return yield over the same period by each of its operating industries. Unfortunately we lose a substantial amount of observation in this step because we require the stock of a diversified firm to have a normal return attached to each of its businesses in order to be included in the analysis. Consistent with the findings of other authors (e.g. Santaló and Becerra, 2008), in our sample periods there were on average 195 four-digits SIC codes per year with no single segment firms operating. If a diversified firm is operating in any of such industries than it is excluded from the sample.

In order to demonstrate that the market has a delayed reaction to related diversification we adopt the following strategy. For every company in the sample we compute the difference between its actual annual return and its normal annual return. If the market has wrongly discounted related diversifiers, we expect that, within this group, those companies that had the most negative performance difference in the previous year will obtain higher abnormal returns in the future.

We conduct this test within the highest group of companies for related diversification calculated following the same procedure adopted for Table 3.6. We divide the companies in this group in two/four portfolios based on the difference between actual and normal return of the company in the previous year. This means that the analysis is run between 1982 and 2007 as we lose one year of observations for the computation of the performance difference.

The results are contained in Table 3.9 for both the division in quartiles of return difference and the division at the median. As it is possible to see, the lower the group of past performance difference the higher and the more significant the alpha (coeff.= 0.80 and t = 3.36 for P-rel for the group below the median; coeff. = 0.511 and t = 2.40 for S-rel for the group below the median). The results support the idea that the underperformance of related diversifiers with respect to their industries is a result of a delayed updating of stock price information.

************************Please insert Table 3.9 about here**************************

3.7 Explaining the relatedness anomaly

3.7.1 Analysts' coverage

In this section we examine three possible explanations that could account for the return predictability found among the group of related diversifiers. We start by investigating whether the abnormal returns could be explained by a lower analysts' coverage. We test this explanation by forming portfolios based on the number of analysts formulating predictions on the EPS of the firm. At the 31st of December of every year between 1980 and 2006 we divide our sample of conglomerates into sixteen portfolios based on independent sorts of analysts' coverage and related diversification. We first assign all the conglomerates that have zero analysts following their stock to a zero portfolio and then we divide the rest of the sample into tertiles of analysts' coverage. We follow the same approach for related diversification. We estimate a four-factor regression (equation (5)) for each of the portfolios built as described. If indeed investors inattention to the stock of related diversifiers is what drives abnormal returns we expect to find positive and significant alphas concentrated at the intersection of low analysts' coverage and high related diversification.

The results are reported in Table 3.10. From the distribution of the alpha coefficients, the hypothesis that the abnormal returns of the portfolio of related diversifiers are due to low analysts coverage is not supported. The only positive and significant alpha for P-rel is in fact found at the intersection of high analysts' coverage and high related diversification (t = 3.06). For S-rel instead, both the alphas of the low analysts' coverage - high related diversification and the high analysts' coverage - high related diversification portfolios are positive and significant (t= 2.15 and t = 2.69). From the persistence of the positive alpha in the high coverage group it seems however that the anomaly is independent from analysts coverage.

***********************Please insert Table 3.10 about here*************************

3.7.2 Relatedness affecting forecasting accuracy

Given that analysts' coverage doesn't seem to matter, as a next step we investigate whether related diversification affect analysts' forecasting ability. In particular, we test whether analysts' forecasts for the group of related diversifiers are negatively biased. Negative biases in EPS forecast would increase the probability of a positive earning surprise and decrease the probability of a negative earning surprise. There is substantial evidence that investors react to earnings surprises by adjusting their portfolios (Keung, Lin, and Shih, 2010; e.g. Della Vigna and Pollet, 2009), a negative bias in EPS forecasts would therefore be consistent with the positive alpha found for the group of related diversifiers.

In order to test whether EPS forecast are biased, we calculate earning surprises as the difference between the actual EPS reported by the firm and the last consensus estimate made available in the year prior to that of the of the EPS announcement. We then define a positive earning surprise dummy that takes the value of 1 in case of a positive earning surprise and 0 otherwise, and a negative earning surprise dummy as the opposite. Using the two dummies as dependent variables we estimate a series of logistic regressions that test the effect of relatedness on earning surprises. We use year dummies and four control variables in the analysis: the natural logarithm of sales, the natural logarithm of the number of patents, the number of analysts estimates on which the consensus is calculated and leverage. Moreover, we alternatively include a structure of sector and firm controls by mean centering all the independent variables at the sector or at the firm level. The timespan of the analysis is between 1980 and 2006, the results are reported in Table 3.11. From the analysis of the coefficients both P-rel and S-rel provide some evidence supporting the hypothesis. In the analyses with sector controls, the coefficient of S-rel is positive and significant in the regression on the positive dummy (coeff. = 0.04; t = 2.68) and negative and significant in the regression on the negative dummy (coeff. = -0.04; t = -2.16). For what concern P-rel instead its effect is only negative and marginally significant on the negative dummy in the analysis with firm controls (coeff. = -1.21; t = -1.83). The rest of the coefficients are in general not significant even though they have consistent signs.

***********************Please insert Table 3.11 about here*************************

3.7.3 Categorical Learning

Starting from the consideration that investors' attention is a scarce resource (Kahneman, 1973), we test whether the relatedness anomaly might be due to investors solving an information overload problem by thinking through categories. Analytical models incorporating this assumption show that the bigger the information overload problem the more the investors will tend to process market and sector-wide information instead of firm-specific information (Peng and Xiong, 2006). The empirical evidence is also consistent with this conclusion (Cooper, Dimitrov, and Rau, 2001).

We use the average sector-wide diversification strategy as a proxy for the kind of sector-wide information that investors might use to judge the diversification strategy of a firm. We calculate this variable as an average by segment sales of the percentage of diversifiers operating in each of the sectors of a conglomerate. Santaló and Becerra (2008) provide evidence that the market valuation of diversifiers depends on the number of competitors following a similar strategy. Whenever a diversified firm operates in sectors dominated by diversifiers than its stock is traded at a premium in comparison to that of focused firms. Vice-versa for the case in which a diversified firm is operating in a sector dominated by focused competitors.

If we assume that on average firms diversification decision are driven by efficiency gains, than this simplified decision process is consistent market prices that are aligned with companies' fundamentals. Nevertheless, whenever this assumption doesn't hold, the same simplified decision process would lead investors to undervalue the stock of related diversifiers operating in sectors dominated by focused competitors. Further this decision process would give rise to abnormal returns to the extent in which investors are surprised by the superior performance obtained by related diversifiers.

To test this idea we form fifteen portfolios based on independent sorts of sector-wide diversification and related diversification. We assign each of the companies in the sample to one of three portfolios calculated as the tertiles of the distribution of the sector-level diversification variable. We form the groups at the 31st of December of the year prior that of the return. We follow the same approach of Table 3.5 to divide the sample into 5 groups of related diversification.

We estimate a four-factor regression (equation (5)) for each of the portfolios built as described; results are reported in Table 3.12. The results provide robust support for the hypothesis that investors use sector-wide information to value the stock of a firm. The alpha is in fact positive and significant only among related diversifiers operating in sectors with a prevalence of single segment firms (t = 3.26 for P-rel; t = 3.54 for S-rel).

***********************Please insert Table 3.12 about here************************

3.8 Robustness checks

3.8.1 The relatedness anomaly over time

Table 3.13 contains the results of four-factors regressions performed on the portfolio of high relatedness and high technological intensity built using the same procedure adopted for Table 3.7. The regressions are run on the monthly risk premium of the portfolio using a ten years rolling window in order to capture possible trends in the anomaly (e.g. the coefficients displayed for year 2000 are obtained form the regression using the data between 1991 and 2000). As is possible to see the alpha coefficient for this portfolio is constantly positive across time. Moreover, the alpha is significant in twelve estimations in the case of P-rel and in nine estimations in the case of S-rel out of the eighteen possible.

***********************Please insert Table 3.13 about here*************************

3.8.2 Six-factors regressions

We estimate six-factors regressions on the value-weighted risk premium of the five related diversification portfolios built using the methodology adopted for Table 3.6. There is evidence that apart from the Market risk premium, Market-to-Book, Size and Momentum, both a Profitability and an Investment factor hold additional power in explaining average returns (Aharoni, Grundy, and Zeng, 2013; Fama and French, 2014; Novy-Marx, 2013). If the portfolios we form differ systematically on any of these two factors we might be attributing to related diversification an explanatory power that it doesn't hold. In order to control for this additional factors we estimate the following regression:

$$(6)\ R_t = \alpha + \beta_1 * RMRF_t + \beta_2 * SmB_{\ t} + \beta_3 * HmL_t + \beta_4 * RmW_t + \beta_5 * CmA_t + \beta_6 * Mom_t + \epsilon_t$$

where R_t is the monthly return of the portfolio in excess of the one month T-bill, $RMRF_t$ is the excess return associated with the market portfolio, and $SmB_{\ t}$ (Small minus Big), HmL_t (High minus Low), RmW (Robust minus Weak), CmA (Conservative minus Aggressive) and Mom_t (Momentum) are the month t returns associated with zero- investment portfolios designed to capture the sensitivity of stock returns to size, book-to-market, profitability, investment and past returns. The alpha of the model represent the abnormal monthly return that is possible to realize by investing in the portfolio once we account for the other factors.

The results are reported in Table 3.14. As it is possible to see the alpha of the high relatedness portfolio is still the only one positive and significant (t = 2.37 for P-rel; t = 2.11 for S-rel)

***********************Please insert Table 3.14 about here*************************

3.9 Conclusions

With few exceptions (e.g. Berger and Ofek, 1995) the finance literature addressing product-market diversification has normally treated it as a unique phenomenon (Campa and Kedia, 2002b; Lang and Stulz, 1994; Villalonga, 2004), disregarding the nature of the inputs on which the diversification strategy is based. Starting from this consideration the aim for this paper is that of addressing the heterogeneity of diversifier. In particular, our analysis focuses on the role of technology and technological relatedness because of the likelihood that this input might give rise to economies of scope (Teece, 1980b, 1982), and because extant evidence suggests that market participants encounter difficulties in evaluating innovation (Cohen *et al.*, 2013).

We show that related diversifiers indeed perform better than the rest of conglomerates but that the performance consequences of their strategy are not fully impounded into the price of their stock. In our sample period the hedge portfolio long on the stock of technology intensive related diversifiers and short on the stock of technology intensive unrelated diversifiers earned abnormal returns of 8.8% per year. This positive effect of related diversification on risk-adjusted returns is present both in value weighted and in equal weighted portfolios and it is particularly strong for big caps. This addresses and excludes the possibility that our findings are due to stocks that are relatively illiquid.

In separate analysis we test three non-competing explanations for our findings: (1) related diversifiers have comparatively lower number of analysts following their stock; (2) related diversification affects the accuracy of analysts' forecasts; (3) the excess returns are only present when the diversification strategy of the firm is somewhat unusual as compared to the norm of the sector. We find support for the third explanation and some support for the second.

In our logistic regressions related diversification increases the probability of positive earning surprises while it decreasing the probability of experiencing negative earning surprises. These effects are consistent with the positive excess return that we find for the portfolio of related diversifiers. Further we find that the positive alpha associated with related diversification is present only when the firm combines in its portfolio of businesses sectors with a high percentage of single segment firms operating. We interpret this finding as evidence that investors tend to punish deviations from the norm by interpreting them as discretional choices that are not justified by a value creation logic.

We argue that our findings open new and interesting avenues for future research. Future work could for example address the role of corporate communication and disclosure in generating consistent expectations in stock market participants about technologically related diversification. Also, it would be interesting to understand whether technological shocks that increase or decrease the similarity in the technological base of two industries are associated with diversification and divestiture moves by companies or whether there is substantial inertia. Finally, scholars might investigate whether other resources that could potentially generate economies of scope, such as a valuable shared brand, are indeed with better performance and with a consistent stock market valuation.

Appendix A

We use four databases for the calculation of the measures of related diversification:

- **Patent-Assignee database**: This is a database from the NBER containing one record for each assignment of each utility patent for the period 1976-2006. Patents that are assigned to more than one party have multiple records. From this database we use three variables: PDPASS, NCLASS and GYEAR. PDPASS is a number that uniquely identifies the patent assignee. NCLASS (only used in the calculation of P-rel) is the main technology class based on the US 3-digit current classification (CCL). This classification is constant across time and therefore it allows us to compare patents obtained in different time periods. Finally GYEAR is the year in which the patent was granted.
- **Patents Citation database**: This is also a database from the NBER. It contains a record for each citing patent – cited patent pair for a total of 24 millions observations. The observations cover the period 1976-2006
- **Dynamic Assignee database:** This is the last database from the NBER that we use. It tracks the ownership of the patents and it allows assigning the right GVKEY to the patents' owners based on PDPASS and GYEAR. The database assumes that when an organization is acquired/merged/spun-off its patents go to the new owner. Using data on mergers and acquisitions of public companies reported in the SDC database, the database dynamically tracks up to 5 corporate ownership

changes, therefore assigning the right GVKEY to each PDPASS depending on the year.

- **Compustat Segment:** We use Compustat Segment to assign a four-digits SIC sector of usage to the patents. Basically we assume that the sector in which a patent is going to be used corresponds to the SIC sector of the patent owner. When the owner is a diversified firm we decompose the weight of the patents between the operating sectors of the firm using the percentage of segment sales.

Calculation of P-rel

P-rel it's a measure of the applicability of firm's patent portfolio to its operating SIC codes. For the calculation of the measure we make use of the Patent-Assignee database, the Dynamic Assignee database and Compustat Segment. The procedure is the following:

- We start with the patent-assignee database and we merge it with the dynamic assignee database in order to assign a GVKEY to each patent based on the year of patent granting
- We merge the file that we obtained with Compustat Segment in order to assign an SIC of usage to each patent.
- Each patent has an initial weight equal to 1. If a patent is assigned to multiple owners operating in different sectors we divide equally the weight of the patent between the sectors in which the owners are operating. If a patent is assigned to a diversified company we divide its weight between the sectors of the company using the percentage of segment sales.

- We use a five year rolling window to calculate the probability that a patent in a given technological class will be used in a given SIC code
- We calculate the stock of patents owned by each firm in each technology class using a five years rolling window
- We multiply the patent stock of a firm in each technology class with the probability distribution of each technology class
- We sum the number that we obtain across technology class at the firm level to obtain a single number returning the applicability of the patent stock to each SIC code and we divide it by the total number of patents in the patent stock of the firm.
- We average by segment sales the number that we obtained in the previous step to obtain a single number with variability between 0 and 1 for each firm.

Comments on the measure: Due to the fact that the measure is a mean of the probability of usage of the patents across sector, the maximum value it can assume is de facto determined by the number of segments. For a company operating in "n" segments and having equal sales across the "n" segments the maximum value of the measure is "1/n".

We believe that this fact does not represent a problem as long as the probability distribution of patent usage is not dependent on the single company. If this were the case, the number of segments of the company would play a key role in determining the value assumed by the measure. However, considering that the probability distribution of patent usage across sector is calculated on all companies and all patents we can assume it to be largely independent from the single case.

Calculation of S-rel

S-rel is a measure that captures the extent to which innovation in one of the sector of a firm can be used as the basis to produce innovation in the other sectors. The measure does not take into account the technological portfolio of a company. We use all the four databases described above to calculate it. The procedure is the following:

- We assign to each citing and cited patent the unique patent assignee number created by the NBER (PDPASS) using the “Patent Assignee” file.
- We assign to each citing and cited patent a GVKEY based on the PDPASS and the year of patent granting using the “Dynamic Assignee” file provided by the NBER.
- We assign to each citing and citing patents an SIC using Compustat segment based on the GVKEY and the year of patent granting.
- Each citation has an initial weigh equal to 1. If a patent is assigned to multiple owners operating in different sectors we divide equally the weight of the citation between the sectors in which the multiple owners are operating. If a patent is assigned to a diversified company we divide the weight of the citation between the sectors of the company using the percentage of segment sales.
- We compute the total amount of cross-citation between sector “A” and sector “B” by summing the weight of all the patents assigned to sector

"A" citing patents assigned to sector "B", and the weight of all the patents assigned to sector "B" citing patents assigned to sector "A" using a five years rolling window.

- We average the total amount of cross-citation at the firm level using the sum of segment sales following the procedure described in the text.

Appendix B

Computing the adjusted measures of performance:

- For every firm in the sample we compute the ROA and the Market to Book and Market to Sales multiples. The ROA is computed as EBIT over sales while the Market to Book and Market to Sales multiples as the market value of the company divided respectively by the book value of the assets and the annual sales. The market value of a company is computed by multiplying the stock price at the end of the year by the number of shares and outstanding and by adding the book value of short-term debt and long-term debt.
- For every four-digits SIC code we compute the industry representative ROA, MtB and MtS ratios as the median value presented by single segment firms in a given year.
- For every firm we compute a normal industry value of ROA, MtB and MtS as the average by segment sales (for ROA and MtS) and segment assets (MtB) of the industry representative values calculated in point 2.

- The adjusted ROA for a company is calculated as the actual ROA – the normal ROA calculated in point 3. The adjusted MtB and MtS instead are calculated as the natural logarithm of the ratio of company's real MtB and MtS multiples and the would be MtB and MtS multiples calculated in point 3.

Adjustments to the final sample:

- We start with a the database resulting from the merge between Compustat Segment, Compustat Annual, the database containing the relatedness measure and that containing the adjusted performance measures.
- We eliminate all firm-year observations with adjusted ROA falling in the 1 and 100 percentile of the overall adjusted ROA distribution.
- We eliminate all firm-year observations with absolute value of Adjusted Market to Book and Market to Sales above 3 (Berger & Ofek, 1995)
- We eliminate all firms with a primary SIC code between 6000 and 7000
- We eliminate all firms in which the total sales (sum of segments sales) differ by the total segment sales used in the calculation of the adjusted Market to Sale by more then 5%. The two numbers might differ if in some of the operating segments are operating only diversified firms.
- We eliminate all firms in which the total assets (sum of segments assets) differ by the total segment assets used in the calculation of the adjusted Market to Book by more then 10%. The two numbers might differ if in some of the operating segments are operating only diversified firms.

- We eliminate all firms with sales below 20 millions

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GRAPH 3.1: CUMULATIVE DISTRIBUTION OF PATENTING ACTIVITY

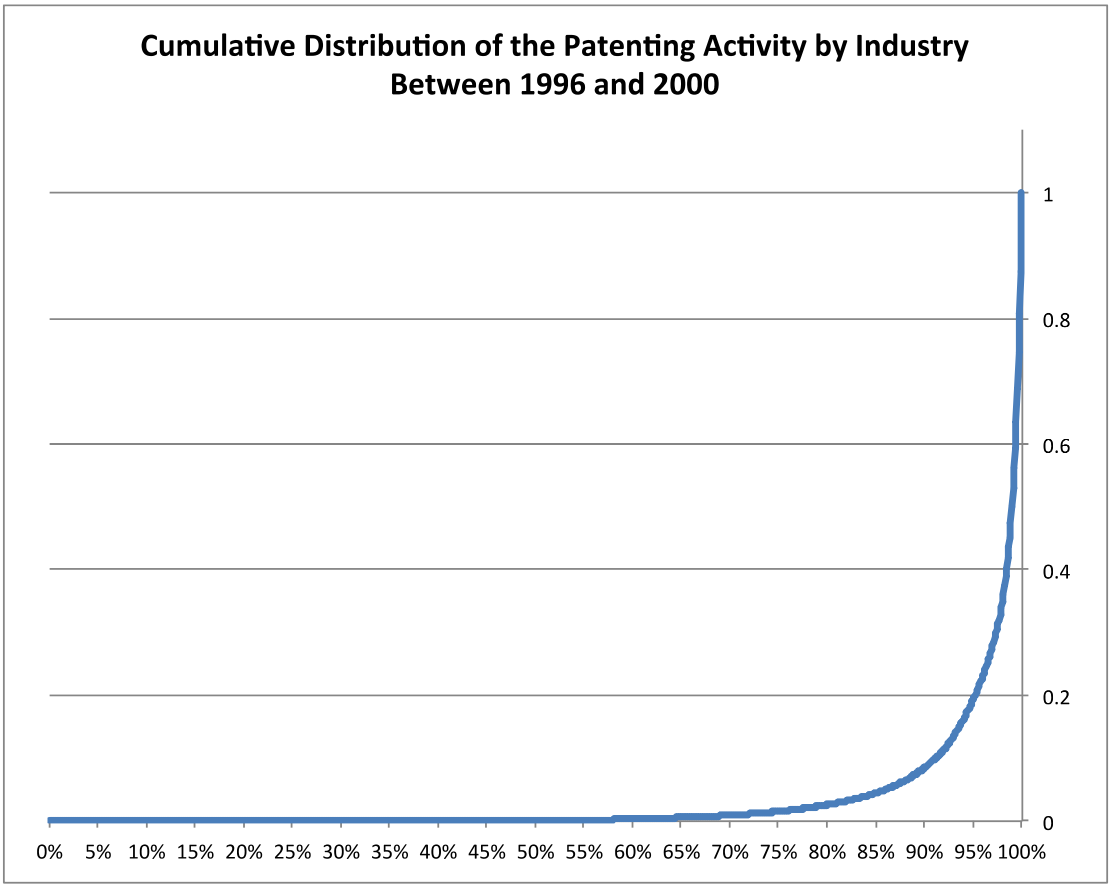

TABLE 3.1

MOST ACTIVE PATENT CLASSES AND SECTOR PAIRS WITH THE HIGHEST CROSS-CITATION

This table contains descriptive statistics for period 1996-2000. In the upper section we report the ten patent classes with the highest number of patent granted and the corresponding sectors in which their applicability is higher. In the lower section instead, we report the ten sector pairs with the highest amount of cross-citation.

10 patent classes with the highest number of patents granted between 1996 and 2000

Patent class	N. patents	Main sector of application	Applicability
438 - Semiconductor device manufacturing: process	6940	3674 - Semiconductors and Related Devices	0.64
514 - Drug, bio-affecting and body treating compositions	6385	2834 - Pharmaceutical Preparations	0.71
257 - Active solid-state devices (e.g., transistors, solid-state diodes)	4689	3674 - Semiconductors and Related Devices	0.52
435 - Chemistry: molecular biology and microbiology	4378	2834 - Pharmaceutical Preparations	0.42
430 - Chemistry: electrical current producing apparatus, product, and process	4089	3861 - Photographic Equipment and Supplies	0.60
428 - Stock material or miscellaneous articles	3539	3861 - Photographic Equipment and Supplies	0.10
370 - Multiplex communications	3492	3663 - Radio and Television Broadcasting and Communications Equipment	0.21
424 - Drug, bio-affecting and body treating compositions	3411	2834 - Pharmaceutical Preparations	0.37
365 - Static information storage and retrieval	3307	3674 - Semiconductors and Related Devices	0.60
455 - Telecommunications	3021	3663 - Radio and Television Broadcasting and Communications Equipment	0.45

10 sector-pairs with the highest amount of cross-citation between 1996 and 2000

Sector 1	Sector 2	Cross-citation
3577 - Computer Peripheral Equipment, NEC	3861 - Photographic Equipment and Supplies	34819
3674 - Semiconductors and Related Devices	3571 - Electronic Computers	14163
3663 - Radio and Television Broadcasting and Communications Equipment	3674 - Semiconductors and Related Devices	13802
3841 - Surgical and Medical Instruments and Apparatus	2834 - Pharmaceutical Preparations	6717
3841 - Surgical and Medical Instruments and Apparatus	3845 - Electromedical and Electrotherapeutic Apparatus	6270
4813 - Telephone Communications, Except Radiotelephone	3661 - Telephone and Telegraph Apparatus	5482
3674 - Semiconductors and Related Devices	3651 - Household Audio and Video Equipment	5163
3674 - Semiconductors and Related Devices	3661 - Telephone and Telegraph Apparatus	4825
3661 - Telephone and Telegraph Apparatus	3663 - Radio and Television Broadcasting and Communications Equipment	4810
4813 - Telephone Communications, Except Radiotelephone	3674 - Semiconductors and Related Devices	4774

TABLE 3.2

RELATEDNESS MEASURE OUTLOOK

This table contains descriptive statistics for the year 2000. In the upper section we report the ten diversified firms with the highest value of P-rel and the corresponding value of S-rel. In the lower section we report the ten diversified firms with the highest value of S-rel and the corresponding value of P-rel.

10 diversified companies with the highest value of P-rel in the year 2000

Company	Main sector	P-rel	S-rel
Astrazeneca Plc	2834 - Pharmaceutical Preparations	0.620	1
Silicon Storage Technology	3674 - Semiconductors and Related Devices	0.555	976
Del Laboratories Inc	2844 - Perfumes, Cosmetics, and Other Toilet Preparations	0.522	2759
Celltech Group Plc	2834 - Pharmaceutical Preparations	0.513	529
King Pharmaceuticals Inc	2834 - Pharmaceutical Preparations	0.454	284
Shire Plc	2834 - Pharmaceutical Preparations	0.449	284
Draxis Health Inc	2834 - Pharmaceutical Preparations	0.440	1540
Roche Holding Ag	2834 - Pharmaceutical Preparations	0.412	734
Adm Tronics Unlimited Inc/De	2891 - Adhesives and Sealants	0.401	29
Bristol-Myers Squibb Co	2834 - Pharmaceutical Preparations	0.373	1222

10 diversified companies with the highest value of S-rel in the year 2000

Company	Main sector	P-rel	S-rel
Canon Inc	3577 - Computer Peripheral Equipment, NEC	0.229	16765
Jds Uniphase Corp	3674 - Semiconductors and Related Devices	0.058	13802
Technicolor Sa	7812 - Motion Picture and Video Tape Production	0.122	6842
Medtronic Plc	3845 - X-Ray Apparatus and Tubes and Related Irradiation Apparatus	0.255	6270
Thoratec Corp	3845 - X-Ray Apparatus and Tubes and Related Irradiation Apparatus	0.131	6270
Datascope Corp	3845 - X-Ray Apparatus and Tubes and Related Irradiation Apparatus	0.209	6270
Sparta Surgical Corp	3841 - Surgical and Medical Instruments and Apparatus	0.000	6270
Escalon Medical Corp	3845 - X-Ray Apparatus and Tubes and Related Irradiation Apparatus	0.087	6270
Remec Inc	3674 - Semiconductors and Related Devices	0.029	6018
Motorola Solutions Inc	3663 - Radio and Television Broadcasting and Communications Equipment	0.151	5412

TABLE 3.3

DESCRIPTIVE STATISTICS

This table provides summary statistics about the sample of diversified firm-years for regression analysis. The sample period is between 1980 and 2006.

	N	Min	Median	Max	Mean	SD
adjROA	22,060	-1.36	0.02	0.49	0.03	0.11
adjMB	22,060	-2.94	-0.15	2.66	-0.17	0.53
adjMS	22,060	-3.00	-0.25	2.99	-0.30	0.75
P-rel	22,060	0	0	0.80	0.02	0.06
S-rel (log)	22,060	0	0.48	10.26	1.55	2.09
Npat	22,060	0	0	16540	65	466
Sales ($ml)	22,060	20	385	285,059	2,829	10,176
Assets ($ml)	22,060	3	389	289,357	3,562	13,862
Leverage	22,060	0	1	23	1	0
HHI	22,060	0.01	0.17	0.96	0.20	0.13

		Correlations									
		1	2	3	4	5	6	7	8	9	10
1	adjROA	1.00									
2	adjMB	0.17	1.00								
3	adjMS	-0.03	0.70	1.00							
4	P-rel	0.18	-0.01	-0.05	1.00						
5	S-rel (log)	0.16	-0.02	-0.03	0.48	1.00					
6	Npat (log)	0.12	-0.01	-0.02	0.53	0.53	1.00				
7	Sales ($ml)	0.04	0.00	0.00	0.18	0.26	0.30	1.00			
8	Assets ($ml)	0.03	-0.02	0.03	0.17	0.25	0.26	0.90	1.00		
9	Leverage	-0.17	-0.06	-0.04	-0.06	-0.05	-0.04	0.06	0.06	1.00	
10	HHI	0.00	-0.03	-0.02	-0.05	-0.11	0.08	-0.03	-0.06	-0.04	1.00

TABLE 3.4

RELATED DIVERSIFICATION, PERFORMANCE AND MARKET VALUATION

This table reports the results of 9 regressions run on both the full sample of firms (only for P-rel) and the subsample of diversified firms. The time span of the sample is between 1980 and 2006. The 6 regressions on the left-hand side test the effect of P-rel, while the 3 regressions on the right-hand side test the effect of S-rel. In the analysis with P-rel we test the effect of related diversification in the full sample trough an interaction with the diversification dummy, given that the measure can be positive also if the company is single segment. The dependent variables are the adjusted ROA, the adjusted Market-to-Book and the Adjusted Market-to-Sales (see appendix B for the adjustment procedure). All the regressions have clustered standard errors at the firm level, firm fixed-effects and year dummy variables. The regressions include as controls the natural logarithm of sales and that of assets to proxy for size, leverage, the Herfindal–Hirschman Index of concentration to proxy for competition and the natural logarithm of the number of patents. T-statistics are reported in parenthesis and statistical significance at the ten, five and one percent level is indicated by +, * and ** respectively.

	P-Rel			S-Rel		
	adjROA (1)	adjMB (2)	adjMS (3)	adjROA (4)	adjMB (5)	adjMS (6)
Lnsale	0.016**	-0.048**		0.016**	-0.048**	
	(6.14)	(-3.74)		(6.19)	(-3.68)	
Lnasset			0.082**			0.083**
			(4.41)			(4.46)
Leverage	-0.043+	-0.047	-0.068+	-0.044+	-0.048	-0.068+
	(-1.83)	(-1.34)	(-1.70)	(-1.83)	(-1.38)	(-1.70)
HHI	0.030*	-0.072	0.039	0.031*	-0.085	0.023
	(1.98)	(-1.01)	(0.37)	(2.07)	(-1.17)	(0.21)
Lnpat	-0.003	-0.023*	-0.040**	-0.001	-0.013	-0.031*
	(-1.36)	(-1.99)	(-2.62)	(-0.55)	(-1.19)	(-2.15)
P-rel	**0.147****	**0.472****	**0.311**			
	(3.81)	**(2.64)**	**(1.35)**			
S-rel				**0.003***	**-0.002**	**-0.008**
				(2.11)	**(-0.34)**	**(-0.85)**
Constant	-0.046*	0.109	-0.601**	-0.048*	0.108	-0.600**
	(-2.32)	(1.46)	(-5.86)	(-2.38)	(1.45)	(-5.84)
N	22060	22060	22060	22060	22060	22060
adj. R-sq	0.039	0.018	0.016	0.037	0.017	0.016

TABLE 3.5

PORTFOLIOS DESCRIPTIVE

This table reports report descriptive statistics for the 5 portfolios of diversified firms built on P-rel in the upper section and for the 5 portfolios of diversified firms built on S-rel in the lower section. The portfolios are calculated at the 31st of December of every year by dividing into quartiles all the firms presenting a positive value of relatedness. All the firms presenting a value of relatedness equal to zero are assigned to the zero portfolios. Statistics about the number of stocks, average monthly value-weighted and average monthly equal-weighted returns are calculated as the average by relatedness portfolio of the 324 months in the period between 1981 and 2007. Statistics about the average capitalization of the stocks in each portfolio are calculated as the average by portfolio of the market capitalization of the stocks at the 31st of December of every year between 1980 and 2006. Statistics about the number of patents and the average P-rel and S-rel also refer to the year prior to that of the monthly return and therefore are calculated on the period between 1980 and 2006.

			P-rel		
	0	1	2	3	4
Stocks in monthly return	636	112	111	111	111
N. patents	0	12	73	205	343
Relatedness	0.0%	0.5%	1.7%	4.3%	15.7%
Capitalization of stocks	1,339,317	1,911,676	2,837,004	4,030,719	7,263,865
Av. monthly ret eq.	1.26%	1.41%	1.41%	1.34%	1.46%
Av. monthly ret val.	1.04%	1.08%	0.81%	0.93%	1.04%
			S-rel		
	0	1	2	3	4
Stocks in monthly return	293	198	198	198	197
N. patents	1	2	7	48	310
Relatedness	0.00	0.14	1.63	24.44	771.84
Capitalization of stocks	1,027,733	1,662,105	1,790,805	2,186,485	6,414,836
Av. monthly ret eq.	1.31%	1.25%	1.34%	1.39%	1.33%
Av. monthly ret val.	1.21%	0.99%	0.94%	0.98%	0.98%

TABLE 3.6

PERFORMANCE ATTRIBUTION REGRESSIONS ON 5 PORTFOLIOS OF S-REL AND P-REL

This table contains the results from the estimation of four-factors regressions (equation (5) from the text) for five portfolios formed on P-rel and five portfolios formed on S-rel. The portfolios are calculated at the 31st of December of every year prior to that of the return by dividing all the firms presenting a positive value of relatedness into quartiles. All the firms presenting a value of relatedness equal to zero are assigned to the zero portfolios. The sample period is between 1981 and 2007. On the left-hand side of the table the regressions are estimated using the monthly value-weighted risk premium of the portfolio as dependent variable (value-weighted return of the portfolio minus the return form the one month T-bill). The value weighting of returns is done based on the market capitalization of a stock in comparison with that of the rest of the stocks falling in the same portfolio. The market capitalization is that exhibited at 31st of December of the year prior to that of the return. On the right-hand side of the table the regressions are estimated using the equal-weighted monthly risk premium of the portfolio as dependent variable. The equal-weighted return of the portfolio is calculated as a simple arithmetic average of the returns of the stocks falling in each portfolio. The last two rows of the table for each relatedness measure contain the results for the hedge portfolios (4-0 and 4-1) calculated using the difference between the returns of the high relatedness portfolio and the returns of the low relatedness portfolios. The control variables are the market risk premium (Mktr-Rf), size (SmB), book-to-market (HmL) and momentum (for further information about these factors refer to Fama and French [1993] and Carhart [1997]). T-statistics are reported in parenthesis and statistical significance at the ten, five and one percent level is indicated by +, * and ** respectively.

	Value Weighted returns						Equal weighted returns					
	Alpha	Mktr - Rf	SmB	H-L	Momentum	adj. R-sq	**Alpha**	Mktr - Rf	SmB	H-L	Momentum	adj. R-sq
P-rel												
0	**-0.131+**	0.993**	-0.023	0.303**	-0.014	0.913	**0.111**	0.989**	0.696**	0.323**	-0.159**	0.922
	(-1.83)	(54.37)	(-1.00)	(11.08)	(-0.88)		**(1.36)**	(47.23)	(26.56)	(10.30)	(-8.49)	
1	**-0.087**	1.112**	0.094*	0.327**	-0.138**	0.826	**0.145**	1.050**	0.698**	0.450**	-0.148**	0.875
	(-0.70)	(35.45)	(2.38)	(6.97)	(-4.91)		**(1.34)**	(38.16)	(20.28)	(10.91)	(-6.00)	
2	**-0.240+**	1.103**	-0.059	0.141**	-0.153**	0.805	**0.236***	1.047**	0.593**	0.350**	-0.173**	0.877
	(-1.77)	(31.92)	(-1.36)	(2.73)	(-4.93)		**(2.22)**	(38.66)	(17.52)	(8.65)	(-7.14)	
3	**0.082**	1.047**	-0.027	-0.073+	-0.249**	0.867	**0.225***	1.064**	0.620**	0.237**	-0.193**	0.908
	(0.72)	(36.51)	(-0.77)	(-1.70)	(-9.68)		**(2.35)**	(43.52)	(20.27)	(6.47)	(-8.80)	
4	**0.291***	0.949**	-0.176**	-0.329**	-0.130**	0.859	**0.394****	1.077**	0.563**	0.130**	-0.199**	0.901
	(2.58)	(33.09)	(-4.90)	(-7.66)	(-5.04)		**(3.84)**	(41.25)	(17.24)	(3.32)	(-8.50)	
4-0	**0.422****	-0.044	-0.153**	-0.632**	-0.115**	0.343	**0.282***	0.088**	-0.133**	-0.193**	-0.040	0.161
	(2.96)	(-1.22)	(-3.37)	(-11.63)	(-3.54)		**(2.59)**	(3.17)	(-3.82)	(-4.65)	(-1.59)	
4-1	**0.377***	-0.163**	-0.269**	-0.656**	0.009	0.231	**0.248***	0.027	-0.135**	-0.320**	-0.051+	0.170
	(2.15)	(-3.66)	(-4.83)	(-9.83)	(0.21)		**(1.99)**	(0.83)	(-3.39)	(-6.71)	(-1.79)	
S-rel												
0	**0.027**	0.978**	-0.025	0.373**	-0.033	0.854	**0.159**	0.966**	0.712**	0.406**	-0.143**	0.878
	(0.29)	(41.21)	(-0.83)	(10.50)	(-1.56)		**(1.58)**	(37.54)	(22.11)	(10.54)	(-6.19)	
1	**-0.263***	1.068**	0.066+	0.355**	-0.002	0.842	**0.034**	1.004**	0.618**	0.440**	-0.123**	0.902
	(-2.43)	(38.76)	(1.93)	(8.60)	(-0.07)		**(0.39)**	(44.76)	(22.01)	(13.11)	(-6.10)	
2	**-0.222+**	1.054**	-0.078*	0.276**	-0.048+	0.814	**0.073**	1.053**	0.604**	0.423**	-0.147**	0.888
	(-1.87)	(34.73)	(-2.04)	(6.07)	(-1.76)		**(0.74)**	(41.54)	(19.03)	(11.14)	(-6.45)	
3	**-0.054**	1.076**	0.025	0.090*	-0.136**	0.849	**0.182+**	1.044**	0.771**	0.247**	-0.171**	0.895
	(-0.46)	(36.53)	(0.67)	(2.03)	(-5.16)		**(1.72)**	(38.64)	(22.82)	(6.11)	(-7.08)	
4	**0.215***	0.971**	-0.141**	-0.248**	-0.187**	0.897	**0.380****	1.056**	0.586**	-0.015	-0.256**	0.900
	(2.28)	(40.47)	(-4.71)	(-6.90)	(-8.68)		**(3.52)**	(38.46)	(17.06)	(-0.37)	(-10.38)	
4-0	**0.188**	-0.006	-0.117*	-0.621**	-0.154**	0.351	**0.220**	0.090*	-0.126**	-0.422**	-0.113**	0.278
	(1.27)	(-0.17)	(-2.47)	(-10.98)	(-4.54)		**(1.56)**	(2.50)	(-2.79)	(-7.84)	(-3.49)	
4-1	**0.477****	-0.096*	-0.208**	-0.603**	-0.185**	0.279	**0.346****	0.052	-0.032	-0.456**	-0.133**	0.326
	(3.04)	(-2.41)	(-4.15)	(-10.06)	(-5.16)		**(2.62)**	(1.54)	(-0.75)	(-9.05)	(-4.40)	

TABLE 3.7

PERFORMANCE ATTRIBUTIONS REGRESSION ON PATENTS-RELATEDNESS PORTFOLIOS

This table contains the results from the estimation of four-factors regressions (equation (5) from the text) for four portfolios built on technologically related diversification using only the subsample of technology intensive firms. We define technology intensive firms to be those firms with an above median number of patents in a given year, calculated only between those firms with a positive number of patents. We divide this sample in four groups using cutoffs determined as the quartiles of the yearly distribution of each related diversification measure. The division into portfolios for either measure is done at the 31st of December of each year prior to that of the returns. The dependent variable is the monthly value-weighted risk premium of the portfolio (value-weighted return of the portfolio minus the return form the one month T-bill). The value weighting of returns is done based on the market capitalization of a stock in comparison with that of the rest of the stocks falling in the same portfolio. The market capitalization is that exhibited at 31st of December of the year prior to that of the return. The last two rows of the table for each relatedness measure contain the results for the hedge portfolio (4-1) calculated using the difference between the returns of the high relatedness portfolio and the returns of the low relatedness portfolio. The control variables are the market risk premium (Mktr-Rf), size (SmB), book-to-market (HmL) and momentum (for further information about these factors refer to Fama and French [1993] and Carhart [1997]). The sample period is between 1981 and 2007. T-statistics are reported in parenthesis and statistical significance at the ten, five and one percent level is indicated by +, * and ** respectively.

	Alpha	Mktr - Rf	SmB	HmL	Momentum	adj. R-sq
P-rel						
1	**-0.337***	1.127**	-0.042	0.222**	-0.088*	0.730
	(-2.03)	(26.61)	(-0.80)	(3.49)	(-2.31)	
2	**-0.076**	1.049**	-0.058	0.011	-0.185**	0.797
	(-0.55)	(29.71)	(-1.31)	(0.20)	(-5.83)	
3	**0.279***	1.037**	-0.168**	-0.077	-0.222**	0.837
	(2.26)	(33.02)	(-4.28)	(-1.63)	(-7.87)	
4	**0.346***	0.946**	-0.198**	-0.436**	-0.168**	0.808
	(2.44)	(26.22)	(-4.38)	(-8.06)	(-5.18)	
4-1	**0.684****	-0.181**	-0.155*	-0.657**	-0.080	0.148
	(3.03)	(-3.15)	(-2.16)	(-7.64)	(-1.55)	
S-rel						
1	**-0.329+**	1.075**	-0.082	0.274**	-0.039	0.629
	(-1.69)	(21.67)	(-1.33)	(3.69)	(-0.88)	
2	**0.031**	1.127**	-0.100+	0.158*	-0.286**	0.736
	(0.18)	(25.50)	(-1.80)	(2.38)	(-7.23)	
3	**-0.045**	1.063**	-0.055	0.021	-0.114**	0.796
	(-0.33)	(30.13)	(-1.25)	(0.40)	(-3.59)	
4	**0.378****	0.951**	-0.211**	-0.381**	-0.198**	0.860
	(3.27)	(32.30)	(-5.74)	(-8.65)	(-7.49)	
4-1	**0.707****	-0.124*	-0.129	-0.655**	-0.158**	0.142
	(2.88)	(-1.98)	(-1.65)	(-6.98)	(-2.82)	

TABLE 3.8

PERFORMANCE ATTRIBUTION REGRESSIONS ON 15 CAPITALIZATION-RELATEDNESS PORTFOLIOS

This table contains the results from the estimation of four-factors regressions (equation (5) from the text) for fifteen portfolios built on independent sorts of market capitalization and relatedness. The portfolios are calculated at the 31st of December of each year prior to that of the return. We divide the sample in three groups of micro, small and big caps based on two cutoff points determined as the 20th and 50th percentile of market capitalization of the NYSE. We assign the sample to five portfolios of relatedness by dividing all the firms presenting a positive value of relatedness into quartiles. All the firms presenting a value of relatedness equal to zero are assigned to the zero portfolios. The dependent variable is the monthly value-weighted risk premium of the portfolio (value-weighted return of the portfolio minus the return form the one month T-bill). The value weighting of returns is done based on the market capitalization of a stock in comparison with that of the rest of the stocks falling in the same portfolio. The market capitalization is that exhibited at 31st of December of the year prior to that of the return. The control variables are the market risk premium (Mktr-Rf), size (SmB), book-to-market (HmL) and momentum (for further information about these factors refer to Fama and French [1993] and Carhart [1997]). The sample period is between 1981 and 2007. T-statistics are reported in parenthesis and statistical significance at the ten, five and one percent level is indicated by +, * and ** respectively.

P-rel						
	Alpha	Mktr - Rf	SmB	H-L	Momentum	adj. R-sq
Micro caps						
0	**0.159**	0.896**	0.901**	0.303**	-0.206**	0.845
	(1.29)	(28.52)	(22.95)	(6.44)	(-7.32)	
1	**0.374***	0.961**	0.941**	0.348**	-0.209**	0.730
	(2.03)	(20.43)	(15.99)	(4.93)	(-4.95)	
2	**0.540***	0.915**	1.047**	0.267**	-0.143**	0.628
	(2.26)	(15.00)	(13.73)	(2.93)	(-2.61)	
3	**0.372**	0.903**	1.209**	0.179+	-0.201**	0.641
	(1.46)	(13.88)	(14.86)	(1.84)	(-3.45)	
4	**0.253**	1.024**	0.934**	0.340**	-0.270**	0.627
	(1.03)	(16.32)	(11.90)	(3.62)	(-4.80)	
Small caps						
0	**-0.090**	0.989**	0.694**	0.338**	-0.133**	0.907
	(-1.01)	(43.42)	(24.33)	(9.92)	(-6.50)	
1	**-0.038**	1.029**	0.812**	0.536**	-0.142**	0.789
	(-0.26)	(27.22)	(17.17)	(9.47)	(-4.20)	
2	**0.166**	0.998**	0.899**	0.383**	-0.149**	0.790
	(1.07)	(25.23)	(18.17)	(6.47)	(-4.19)	
3	**0.153**	1.009**	0.788**	0.195**	-0.127**	0.801
	(1.00)	(25.99)	(16.22)	(3.35)	(-3.64)	
4	**0.641****	1.103**	0.934**	0.174*	-0.174**	0.755
	(3.24)	(21.87)	(14.81)	(2.30)	(-3.84)	
Big caps						
0	**-0.130+**	0.992**	-0.078**	0.298**	-0.003	0.903
	(-1.72)	(51.51)	(-3.22)	(10.33)	(-0.20)	
1	**-0.196**	1.112**	0.042	0.330**	-0.075*	0.755
	(-1.30)	(29.03)	(0.87)	(5.75)	(-2.19)	
2	**-0.189**	1.097**	-0.136**	0.071	-0.204**	0.817
	(-1.41)	(32.32)	(-3.21)	(1.39)	(-6.71)	
3	**0.085**	1.071**	-0.054	-0.069	-0.239**	0.854
	(0.71)	(34.91)	(-1.40)	(-1.50)	(-8.67)	
4	**0.300****	0.933**	-0.181**	-0.329**	-0.136**	0.856
	(2.67)	(32.62)	(-5.06)	(-7.70)	(-5.31)	

S-rel						
	Alpha	Mktr - Rf	SmB	H-L	Momentum	adj. R-sq
Micro caps						
0	**0.102**	0.874**	0.906**	0.368**	-0.133**	0.792
	(0.72)	(24.23)	(20.10)	(6.82)	(-4.10)	
1	**0.039**	0.918**	0.911**	0.395**	-0.200**	0.793
	(0.27)	(24.62)	(19.54)	(7.08)	(-5.99)	
2	**0.354+**	0.954**	0.812**	0.389**	-0.225**	0.702
	(1.91)	(20.21)	(13.75)	(5.51)	(-5.32)	
3	**0.239**	0.936**	1.002**	0.267**	-0.202**	0.753
	(1.34)	(20.57)	(17.61)	(3.92)	(-4.94)	
4	**0.584***	0.944**	1.152**	-0.018	-0.376**	0.723
	(2.55)	(16.19)	(15.80)	(-0.21)	(-7.20)	
Small caps						
0	**-0.076**	0.948**	0.651**	0.429**	-0.155**	0.816
	(-0.62)	(30.19)	(16.57)	(9.11)	(-5.51)	
1	**-0.116**	1.002**	0.710**	0.456**	-0.107**	0.825
	(-0.91)	(31.12)	(17.64)	(9.46)	(-3.70)	
2	**0.023**	1.047**	0.665**	0.454**	-0.165**	0.838
	(0.18)	(33.05)	(16.79)	(9.58)	(-5.80)	
3	**0.059**	1.036**	0.970**	0.259**	-0.106**	0.860
	(0.44)	(30.74)	(23.02)	(5.13)	(-3.51)	
4	**0.172**	1.067**	0.932**	-0.039	-0.133**	0.808
	(0.98)	(23.82)	(16.63)	(-0.58)	(-3.30)	
Big caps						
0	**0.038**	0.980**	-0.090**	0.370**	-0.019	0.841
	(0.38)	(39.33)	(-2.90)	(9.92)	(-0.83)	
1	**-0.331****	1.063**	0.006	0.302**	0.002	0.797
	(-2.63)	(33.16)	(0.16)	(6.29)	(0.08)	
2	**-0.160**	1.074**	-0.100**	0.323**	-0.039	0.829
	(-1.40)	(37.03)	(-2.76)	(7.45)	(-1.50)	
3	**-0.103**	1.095**	-0.074+	0.042	-0.162**	0.847
	(-0.86)	(35.89)	(-1.94)	(0.93)	(-5.92)	
4	**0.233***	0.957**	-0.154**	-0.264**	-0.181**	0.891
	(2.42)	(38.97)	(-5.00)	(-7.17)	(-8.23)	

TABLE 3.9

PERFORMANCE ATTRIBUTION REGRESSIONS ON PORTFOLIOS OF RELATEDNESS AND PRIOR PERFORMANCE

This table contains the results from the estimation of four-factors regressions (equation (5) from the text) on monthly value-weighted returns for two and four portfolios of related diversifiers built on past performance differential with regard to the industry. We start by forming five portfolios of related diversification that are recalculated at the 31st of December of every year prior to that of the return by dividing all the diversified firms presenting a positive value of relatedness into quartiles. All the diversified firms presenting a value of relatedness equal to zero are assigned to the zero portfolios. Of the five portfolios we keep only the highest portfolio of related diversification. For each firm we calculate the annual normal return due to the industry and we subtract it from the actual return of the firm. We calculate the normal return of an industry by forming value-weighed portfolios of single-segment firms based on the four-digits SIC code. The portfolios are formed every year based on the SIC code reported by the single segment firms in the year of the return. The value weighting of returns is done based on the market capitalization of the stock in comparison with that of the rest of the stocks falling in the same portfolio. The market capitalization is that exhibited by the stock at the 31st of December of the year prior to that of the return. The normal return for a diversified company is the weighted average by segment sales of the normal return attached to each of its segments. We divide the remaining sample of related diversifiers at the median/in quartile of the difference between the actual annual return obtained by the company and the normal annual return due to its industries in the previous year. The control variables are the market risk premium (Mktr-Rf), size (SmB), book-to-market (HmL) and momentum (for further information about these factors refer to Fama and French [1993] and Carhart [1997]). The sample period is between 1982 and 2007. T-statistics are reported in parenthesis and statistical significance at the ten, five and one percent level is indicated by +, * and ** respectively.

P-rel

	Alpha	Mktr - Rf	SmB	HmL	Momentum	adj. R-sq
Two portfolios						
1	**0.797****	0.935**	-0.021	-0.415**	-0.273**	0.620
	(3.36)	(15.59)	(-0.27)	(-4.60)	(-5.06)	
2	**0.044**	1.033**	-0.142*	-0.377**	-0.162**	0.689
	(0.21)	(19.52)	(-2.13)	(-4.73)	(-3.40)	
Four portfolios						
1	**0.790***	1.013**	0.209+	-0.300*	-0.428**	0.489
	(2.32)	(11.76)	(1.93)	(-2.31)	(-5.52)	
2	**0.600***	0.966**	-0.166*	-0.403**	-0.154**	0.592
	(2.44)	(15.55)	(-2.13)	(-4.31)	(-2.76)	
3	**0.139**	1.066**	-0.160+	-0.304**	-0.226**	0.597
	(0.54)	(16.29)	(-1.95)	(-3.09)	(-3.84)	
4	**-0.016**	1.120**	-0.008	-0.393**	-0.093	0.549
	(-0.05)	(14.49)	(-0.08)	(-3.38)	(-1.33)	

S-rel

	Alpha	Mktr - Rf	SmB	HmL	Momentum	adj. R-sq
Two portfolios						
1	**0.511***	1.036**	0.115+	-0.333**	-0.353**	0.708
	(2.40)	(19.25)	(1.70)	(-4.11)	(-7.29)	
2	**0.272**	0.992**	-0.167**	-0.356**	-0.213**	0.752
	(1.57)	(22.67)	(-3.04)	(-5.40)	(-5.40)	
Four portfolios						
1	**0.514+**	1.039**	0.239**	-0.078	-0.408**	0.547
	(1.78)	(14.25)	(2.61)	(-0.71)	(-6.22)	
2	**0.453+**	1.117**	0.030	-0.516**	-0.320**	0.668
	(1.75)	(17.09)	(0.37)	(-5.25)	(-5.44)	
3	**0.274**	1.027**	-0.289**	-0.247**	-0.342**	0.671
	(1.27)	(18.81)	(-4.21)	(-3.01)	(-6.96)	
4	**0.389**	1.001**	0.016	-0.383**	-0.090	0.609
	(1.58)	(16.08)	(0.20)	(-4.09)	(-1.61)	

TABLE 3.10

PERFORMANCE ATTRIBUTION REGRESSIONS ON 16 PORTFOLIOS OF NUMBER OF ANALYSTS AND RELATEDNESS

This table contains the results from the estimation of four-factors regressions (equation (5) from the text) on monthly value-weighted returns for sixteen portfolios of diversified companies built on independent sorts of number of analysts and relatedness. The portfolios are calculated at the 31st of December of each year. We assign all the firms with zero analysts' EPS estimates to a zero portfolio and we divide the rest of the sample with a positive value of number of analysts' estimates into tertiles. We follow the same procedure to assign the firms in the sample to relatedness portfolios. The dependent variable is the monthly value-weighted risk premium of the portfolio (value-weighted return of the portfolio minus the return form the one month T-bill). The value weighting of returns is done based on the market capitalization of a stock in comparison with that of the rest of the stocks falling in the same portfolio. The market capitalization is that exhibited at 31st of December of the year prior to that of the return. The control variables are the market risk premium (Mktr-Rf), size (SmB), book-to-market (HmL) and momentum (for further information about these factors refer to Fama and French [1993] and Carhart [1997]). The sample period is between 1981 and 2007. T-statistics are reported in parenthesis and statistical significance at the ten, five and one percent level is indicated by +, * and ** respectively.

P-rel						
	Alpha	Mktr - Rf	SmB	H-L	Momentum	adj. R-sq
Zero estimates						
0	**-0.202+**	0.991**	-0.089**	0.263**	-0.006	0.833
	(-1.94)	(37.40)	(-2.69)	(6.64)	(-0.24)	
1	**-0.196**	1.079**	0.089	0.203**	-0.302**	0.704
	(-1.08)	(23.34)	(1.53)	(2.93)	(-7.29)	
2	**-0.054**	1.070**	-0.039	0.031	-0.382**	0.599
	(-0.23)	(17.44)	(-0.51)	(0.34)	(-6.94)	
3	**0.052**	1.081**	0.038	-0.405**	-0.345**	0.691
	(0.23)	(18.72)	(0.52)	(-4.68)	(-6.67)	
Low num. of estimates						
0	**-0.180**	0.963**	0.426**	0.305**	-0.064*	0.803
	(-1.47)	(30.74)	(10.88)	(6.51)	(-2.28)	
1	**-0.386***	1.014**	0.742**	0.583**	-0.084*	0.718
	(-2.27)	(23.42)	(13.71)	(9.00)	(-2.17)	
2	**0.175**	0.971**	0.770**	0.300**	-0.089*	0.683
	(0.90)	(19.67)	(12.47)	(4.06)	(-2.00)	
3	**0.310**	0.900**	0.768**	0.132+	-0.045	0.649
	(1.49)	(16.98)	(11.58)	(1.66)	(-0.95)	
Medium num. of estimates						
0	**-0.145**	1.038**	0.294**	0.320**	-0.069**	0.831
	(-1.25)	(35.28)	(7.98)	(7.27)	(-2.61)	
1	**-0.016**	1.140**	0.413**	0.406**	-0.099**	0.762
	(-0.10)	(28.14)	(8.14)	(6.70)	(-2.72)	
2	**0.076**	1.127**	0.249**	0.323**	-0.190**	0.743
	(0.46)	(26.69)	(4.72)	(5.11)	(-5.02)	
3	**-0.018**	1.054**	0.568**	0.225**	-0.066+	0.735
	(-0.10)	(23.84)	(10.26)	(3.40)	(-1.66)	
High num. of estimates						
0	**-0.100**	1.001**	-0.066*	0.324**	-0.009	0.863
	(-1.08)	(42.53)	(-2.23)	(9.21)	(-0.45)	
1	**-0.216**	1.111**	0.016	0.413**	-0.010	0.671
	(-1.21)	(24.40)	(0.28)	(6.07)	(-0.24)	
2	**-0.100**	1.072**	-0.085*	-0.048	-0.132**	0.824
	(-0.77)	(32.21)	(-2.03)	(-0.95)	(-4.43)	
3	**0.334****	0.961**	-0.239**	-0.266**	-0.141**	0.863
	(3.06)	(34.60)	(-6.88)	(-6.41)	(-5.66)	

S-rel

	Alpha	Mktr - Rf	SmB	H-L	Momentum	adj. R-sq
Zero estimates						
0	**0.151**	0.991**	0.026	0.344**	-0.124**	0.679
	(0.94)	(24.10)	(0.51)	(5.58)	(-3.36)	
1	**-0.398****	1.033**	-0.088+	0.216**	-0.029	0.724
	(-2.62)	(26.63)	(-1.82)	(3.72)	(-0.82)	
2	**-0.210**	1.121**	-0.016	0.121*	-0.027	0.774
	(-1.40)	(29.33)	(-0.34)	(2.11)	(-0.80)	
3	**0.051**	1.053**	-0.004	-0.201**	-0.342**	0.751
	(0.29)	(23.30)	(-0.06)	(-2.97)	(-8.43)	
Low num. of estimates						
0	**-0.137**	0.937**	0.477**	0.443**	-0.031	0.698
	(-0.89)	(23.79)	(9.69)	(7.52)	(-0.87)	
1	**-0.103**	0.954**	0.543**	0.498**	-0.051	0.749
	(-0.73)	(26.68)	(12.14)	(9.30)	(-1.59)	
2	**-0.388***	1.067**	0.561**	0.366**	-0.146**	0.737
	(-2.30)	(24.77)	(10.41)	(5.67)	(-3.77)	
3	**0.456***	0.836**	0.665**	-0.155+	-0.036	0.649
	(2.15)	(15.51)	(9.86)	(-1.92)	(-0.74)	
Medium num. of estimates						
0	**-0.040**	1.030**	0.335**	0.397**	-0.038	0.751
	(-0.28)	(28.02)	(7.28)	(7.22)	(-1.17)	
1	**-0.154**	1.053**	0.313**	0.359**	-0.028	0.770
	(-1.09)	(29.38)	(6.98)	(6.69)	(-0.88)	
2	**0.025**	1.043**	0.319**	0.291**	-0.180**	0.807
	(0.19)	(31.42)	(7.69)	(5.86)	(-6.04)	
3	**-0.010**	1.132**	0.467**	0.284**	-0.117**	0.788
	(-0.06)	(28.87)	(9.52)	(4.84)	(-3.34)	
High num. of estimates						
0	**0.030**	1.042**	-0.105*	0.367**	-0.005	0.779
	(0.24)	(32.10)	(-2.58)	(7.55)	(-0.16)	
1	**-0.249+**	1.088**	0.009	0.427**	-0.006	0.734
	(-1.66)	(28.49)	(0.20)	(7.48)	(-0.17)	
2	**-0.228+**	1.044**	-0.032	0.238**	-0.055+	0.772
	(-1.68)	(30.22)	(-0.73)	(4.61)	(-1.76)	
3	**0.263****	0.975**	-0.203**	-0.240**	-0.146**	0.888
	(2.69)	(39.24)	(-6.55)	(-6.46)	(-6.54)	

TABLE 3.11

LOGISTICS REGRESSIONS ON EARNING SURPRISES

This table contains the results of a series of logistic regression returning the probability that a firm will experience a positive (negative) earning surprise as a function of related diversification. We calculate earning surprises as the difference between the actual EPS reported by the firm and the last consensus (median) estimate made available in the year prior to that of the EPS. The dependent variable, positive (negative), is a dummy variable that takes the value of 1 if the company reported an EPS above (below) the consensus estimate, and 0 otherwise. On the upper section of the table we impose a structure of sector controls by subtracting from the actual value of each variable the mean value of the variable calculated by four-digits SIC. On the lower section of the table instead we impose a structure of firm controls by mean centering the independent variables at the firm level. All the logistics regressions include year dummy variables. Moreover, we use as controls the natural logarithm of sales and of number of patents, leverage, the number of analysts following the company and a diversification dummy. The sample period is between 1980 and 2006. T-statistics are reported in parenthesis and statistical significance at the ten, five and one percent level is indicated by +, * and ** respectively.

	Sector			
	Positive	Positive	Negative	Negative
Npat	0.016	0.008	-0.019	-0.010
	(0.95)	(0.50)	(-1.04)	(-0.55)
Sales	0.139**	0.137**	-0.137**	-0.136**
	(6.89)	(6.82)	(-6.61)	(-6.57)
Leverage	-0.549**	-0.538**	0.630**	0.620**
	(-4.91)	(-4.83)	(5.53)	(5.44)
N. analysts	-0.001	-0.001	-0.008*	-0.008*
	(-0.16)	(-0.13)	(-2.05)	(-2.06)
S-rel		**0.041****		**-0.035***
		(2.68)		**(-2.16)**
P-rel	**0.573**		**-0.318**	
	(1.29)		**(-0.68)**	
Constant	0.083	0.064	-0.317**	-0.300**
	(1.17)	(0.90)	(-4.34)	(-4.09)
N	14600	14600	14600	14600

	Firm			
	Positive	Positive	Negative	Negative
Npat	-0.028 (-0.69)	-0.028 (-0.68)	0.034 (0.81)	0.025 (0.61)
Sales	0.067 (1.33)	0.057 (1.12)	-0.093+ (-1.79)	-0.084 (-1.60)
Leverage	-0.628** (-3.43)	-0.633** (-3.44)	0.704** (3.79)	0.711** (3.83)
N. analysts	-0.017* (-2.49)	-0.016* (-2.34)	0.013* (1.97)	0.012+ (1.80)
S-rel		**0.030** **(1.13)**		**-0.030** **(-1.08)**
P-rel	**0.735** **(1.08)**		**-1.214+** **(-1.83)**	
Constant	0.156* (2.13)	0.153* (2.09)	-0.369** (-4.94)	-0.366** (-4.90)
N	14600	14600	14600	14600

TABLE 3.12

PERFORMANCE ATTRIBUTION REGRESSION ON 15 PORTFOLIOS OF AVERAGE DIVERSIFICATION IN THE SECTOR AND RELATEDNESS

This table contains the results from the estimation of four-factors regressions (equation (5) from the text) on the monthly value-weighted risk-premiums of fifteen portfolios of diversified companies built on independent sorts of the average percentage of diversifiers and related diversification. The portfolios are calculated at the 31st of December of each year. For every firm in the sample we calculate the percentage of diversified competitors as the average by segments sales of the percentage of diversified companies in each of the operating four-digits SIC code. We divide the sample in tertiles based on the distribution of this variable. We assign the sample to five portfolios of relatedness by dividing all the firms presenting a positive value of relatedness into quartiles. All the firms presenting a value of relatedness equal to zero are assigned to the zero portfolios. The dependent variable is the monthly value-weighted risk premium of the portfolio (value-weighted return of the portfolio minus the return form the one month T-bill). The value weighting of returns is done based on the market capitalization of a stock in comparison with that of the rest of the stocks falling in the same portfolio. The market capitalization is that exhibited at 31st of December of the year prior to that of the return. The control variables are the market risk premium (Mktr-Rf), size (SmB), book-to-market (HmL) and momentum (for further information about these factors refer to Fama and French [1993] and Carhart [1997]). The sample period is between 1981 and 2007. T-statistics are reported in parenthesis and statistical significance at the ten, five and one percent level is indicated by +, * and ** respectively.

P-rel

	Alpha	Mktr - Rf	SmB	H-L	Momentum	adj. R-sq
Low Div						
0	**-0.034**	1.046**	0.155**	0.145**	-0.086**	0.831
	(-0.28)	(34.37)	(4.07)	(3.18)	(-3.14)	
1	**0.128**	1.046**	0.225**	0.276**	-0.166**	0.623
	(0.63)	(20.16)	(3.47)	(3.55)	(-3.56)	
2	**-0.160**	1.087**	0.109	-0.174+	-0.244**	0.636
	(-0.68)	(18.12)	(1.45)	(-1.93)	(-4.54)	
3	**0.377+**	1.056**	-0.017	-0.548**	-0.347**	0.714
	(1.72)	(18.86)	(-0.24)	(-6.54)	(-6.91)	
4	**0.465****	0.926**	-0.221**	-0.511**	-0.129**	0.807
	(3.26)	(25.47)	(-4.86)	(-9.40)	(-3.96)	
Medium Div						
0	**-0.190**	0.932**	-0.151**	0.333**	-0.009	0.774
	(-1.64)	(31.59)	(-4.09)	(7.53)	(-0.34)	
1	**-0.099**	1.127**	0.048	0.248**	-0.169**	0.723
	(-0.57)	(25.73)	(0.87)	(3.78)	(-4.30)	
2	**-0.124**	1.118**	-0.141*	0.130+	-0.238**	0.681
	(-0.63)	(22.50)	(-2.28)	(1.75)	(-5.34)	
3	**0.211**	1.030**	-0.115*	0.216**	-0.087*	0.717
	(1.35)	(25.93)	(-2.32)	(3.64)	(-2.43)	
4	**-0.030**	0.934**	-0.015	0.235**	-0.053	0.516
	(-0.14)	(17.09)	(-0.21)	(2.87)	(-1.08)	
High Div						
0	**-0.157**	1.044**	0.028	0.372**	0.022	0.790
	(-1.27)	(33.08)	(0.72)	(7.88)	(0.77)	
1	**-0.060**	1.074**	0.252**	0.542**	-0.079+	0.666
	(-0.34)	(23.81)	(4.46)	(8.02)	(-1.95)	
2	**-0.282**	1.073**	0.013	0.317**	-0.119**	0.636
	(-1.46)	(21.79)	(0.21)	(4.31)	(-2.69)	
3	**-0.188**	1.092**	0.009	0.428**	-0.127**	0.715
	(-1.17)	(26.61)	(0.18)	(6.97)	(-3.46)	
4	**0.131**	1.083**	-0.059	0.295**	-0.186**	0.688
	(0.74)	(24.04)	(-1.04)	(4.37)	(-4.61)	

S-rel

	Alpha	Mktr - Rf	SmB	H-L	Momentum	adj. R-sq
Low Div						
0	**0.040**	1.024**	0.060	0.314**	-0.090**	0.740
	(0.28)	(27.84)	(1.30)	(5.71)	(-2.72)	
1	**-0.248**	1.221**	0.222**	0.267**	-0.044	0.649
	(-1.12)	(21.64)	(3.14)	(3.16)	(-0.87)	
2	**-0.327**	1.044**	0.165*	0.045	-0.146**	0.642
	(-1.58)	(19.86)	(2.51)	(0.57)	(-3.10)	
3	**-0.087**	1.176**	0.151	-0.189+	-0.173*	0.562
	(-0.29)	(15.68)	(1.61)	(-1.69)	(-2.58)	
4	**0.483****	0.912**	-0.198**	-0.511**	-0.188**	0.821
	(3.54)	(26.22)	(-4.54)	(-9.82)	(-6.03)	
Medium Div						
0	**-0.117**	0.941**	-0.082+	0.400**	0.003	0.700
	(-0.84)	(26.54)	(-1.85)	(7.54)	(0.10)	
1	**-0.374****	0.992**	0.016	0.400**	-0.018	0.720
	(-2.64)	(27.49)	(0.34)	(7.40)	(-0.56)	
2	**0.011**	1.007**	-0.184**	0.179**	-0.083*	0.715
	(0.07)	(25.63)	(-3.74)	(3.04)	(-2.35)	
3	**-0.074**	1.077**	-0.039	0.142*	-0.123**	0.726
	(-0.45)	(25.71)	(-0.75)	(2.26)	(-3.26)	
4	**0.016**	0.971**	-0.199**	0.159**	-0.114**	0.713
	(0.11)	(25.24)	(-4.14)	(2.75)	(-3.32)	
High Div						
0	**0.084**	0.970**	-0.016	0.381**	0.015	0.715
	(0.60)	(27.29)	(-0.36)	(7.17)	(0.47)	
1	**-0.187**	1.030**	0.078	0.393**	0.076*	0.707
	(-1.23)	(26.61)	(1.60)	(6.79)	(2.18)	
2	**-0.382+**	1.060**	0.086	0.442**	-0.011	0.590
	(-1.89)	(20.59)	(1.33)	(5.73)	(-0.24)	
3	**-0.156**	1.090**	0.095*	0.305**	-0.154**	0.764
	(-1.06)	(29.04)	(2.02)	(5.43)	(-4.58)	
4	**-0.110**	1.080**	-0.068	0.371**	-0.150**	0.733
	(-0.71)	(27.45)	(-1.39)	(6.31)	(-4.25)	

TABLE 3.13

ABNORMAL RETURNS TO RELATED DIVERSIFICATION OVER TIME

This table contains the results from the estimation of four-factors regressions (equation (5) from the text) on the monthly value-weighted risk-premiums of the highest portfolios for both patents and relatedness built following the procedure described in table 3.6. The portfolios are calculated at the 31st of December of each year. The analysis is run using a ten years rolling (e.g. the coefficients for the year 2000 are estimated on the time series of monthly risk premiums between 1991 and 2000). The dependent variable is the monthly value-weighted risk premium of the portfolio (value-weighted return of the portfolio minus the return form the one month T-bill). The value weighting of returns is done based on the market capitalization of a stock in comparison with that of the rest of the stocks falling in the same portfolio. The market capitalization is that exhibited at 31st of December of the year prior to that of the return. The control variables are the market risk premium (Mktr-Rf), size (SmB), book-to-market (HmL) and momentum (for further information about these factors refer to Fama and French [1993] and Carhart [1997]). The sample period is between 1981 and 2007. T-statistics are reported in parenthesis and statistical significance at the ten, five and one percent level is indicated by +, * and ** respectively.

P-rel	**Year**	**Alpha**	**Mktr - Rf**	**SmB**	**H-L**	**Momentum**	**adj. R-sq**
	1990	**0.224**	0.952**	-0.365**	-0.230**	-0.034	0.925
	1991	**0.216+**	0.969**	-0.326**	-0.178**	-0.016	0.935
	1992	**0.224+**	0.986**	-0.289**	-0.157**	0.012	0.930
	1993	**0.273***	0.965**	-0.283**	-0.226**	-0.022	0.923
	1994	**0.346****	0.956**	-0.290**	-0.237**	-0.011	0.926
	1995	**0.328****	0.962**	-0.290**	-0.262**	-0.019	0.926
	1996	**0.278***	0.958**	-0.261**	-0.248**	-0.040	0.917
	1997	**0.301***	0.953**	-0.266**	-0.236**	-0.041	0.881
	1998	**0.408****	0.919**	-0.292**	-0.201**	-0.080	0.879
	1999	**0.429***	0.907**	-0.276**	-0.153*	-0.126*	0.837
	2000	**0.343**	0.859**	-0.162**	-0.347**	-0.088	0.766
	2001	**0.445+**	0.892**	-0.128*	-0.355**	-0.186**	0.788
	2002	**0.517***	0.904**	-0.133*	-0.392**	-0.225**	0.826
	2003	**0.450+**	0.885**	-0.150*	-0.421**	-0.203**	0.825
	2004	**0.355**	0.903**	-0.125+	-0.395**	-0.189**	0.815
	2005	**0.368**	0.909**	-0.126+	-0.394**	-0.189**	0.813
	2006	**0.349**	0.902**	-0.121+	-0.410**	-0.186**	0.811
	2007	**0.264**	0.900**	-0.106	-0.424**	-0.188**	0.808

S-rel	**Year**	**Alpha**	**Mktr - Rf**	**SmB**	**H-L**	**Momentum**	**adj. R-sq**
	1990	**0.160**	0.958**	-0.327**	-0.261**	-0.078*	0.941
	1991	**0.156**	0.975**	-0.301**	-0.205**	-0.058	0.946
	1992	**0.136**	0.998**	-0.277**	-0.174**	-0.041	0.939
	1993	**0.219**	0.983**	-0.287**	-0.236**	-0.079+	0.920
	1994	**0.302***	0.981**	-0.300**	-0.221**	-0.075+	0.918
	1995	**0.266***	0.987**	-0.286**	-0.224**	-0.071	0.915
	1996	**0.233+**	0.986**	-0.274**	-0.202**	-0.078	0.905
	1997	**0.246+**	0.978**	-0.288**	-0.200**	-0.082+	0.876
	1998	**0.336***	0.955**	-0.303**	-0.126+	-0.150**	0.874
	1999	**0.401***	0.937**	-0.260**	-0.105	-0.165**	0.853
	2000	**0.280**	0.910**	-0.153**	-0.239**	-0.122*	0.801
	2001	**0.378+**	0.946**	-0.111+	-0.269**	-0.252**	0.829
	2002	**0.495***	0.949**	-0.123*	-0.313**	-0.287**	0.867
	2003	**0.390+**	0.936**	-0.137*	-0.333**	-0.257**	0.870
	2004	**0.291**	0.949**	-0.111*	-0.310**	-0.244**	0.862
	2005	**0.297**	0.954**	-0.114*	-0.310**	-0.244**	0.862
	2006	**0.265**	0.948**	-0.109+	-0.332**	-0.244**	0.861
	2007	**0.242**	0.931**	-0.100+	-0.362**	-0.250**	0.857

TABLE 3.14

SIX-FACTORS PERFORMANCE ATTRIBUTION REGRESSIONS

This table contains the results from the estimation of six-factors regressions (equation (6) from the text) on the monthly value-weighted risk-premiums of five portfolios of diversified firms built on relatedness. The portfolios are calculated at the 31st of December of each year by dividing all the firms in the sample with a positive value of relatedness into quartiles. All the firms having a value of relatedness equal to zero are assigned to a zero portfolio. The dependent variable is the monthly value-weighted risk premium of the portfolio (value-weighted return of the portfolio minus the return form the one month T-bill). The value weighting of returns is done based on the market capitalization of a stock in comparison with that of the rest of the stocks falling in the same portfolio. The market capitalization is that exhibited at 31st of December of the year prior to that of the return. The control variables are the market risk premium (Mktr-Rf), size (SmB), book-to-market (HmL), profitability (RmW), investment (CmA) and momentum (for further information about these factors refer to Fama and French [1993, 2014] and Carhart [1997]). The Monthly risk premium associated with the profitability and investment factors come from Kenneth French website. The sample period is between 1981 and 2007. T-statistics are reported in parenthesis and statistical significance at the ten, five and one percent level is indicated by +, * and ** respectively.

	Alpha	Mktr - Rf	SmB	HmL	RmW	CmA	Momentum	adj. R-sq
P-rel								
0	**-0.161***	0.996**	0.029	0.299**	0.099**	-0.016	-0.021	0.915
	(-2.23)	(53.66)	(1.17)	(8.26)	(3.02)	(-0.33)	(-1.28)	
1	**-0.141**	1.126**	0.134**	0.239**	0.081	0.147+	-0.149**	0.829
	(-1.13)	(35.21)	(3.14)	(3.84)	(1.44)	(1.75)	(-5.26)	
2	**-0.316***	1.120**	-0.000	0.068	0.149*	0.124	-0.167**	0.807
	(-2.29)	(31.65)	(-0.00)	(0.99)	(2.39)	(1.33)	(-5.32)	
3	**0.089**	1.051**	-0.077*	-0.102+	-0.105*	0.111	-0.245**	0.870
	(0.78)	(36.03)	(-1.99)	(-1.78)	(-2.03)	(1.45)	(-9.51)	
4	**0.267***	0.961**	-0.234**	-0.379**	-0.055	0.167*	-0.130**	0.865
	(2.37)	(33.29)	(-6.08)	(-6.74)	(-1.08)	(2.20)	(-5.09)	
	Alpha	Mktr - Rf	SmB	HmL	RmW	CmA	Momentum	adj. R-sq
S-rel								
0	**-0.050**	0.988**	0.083**	0.337**	0.244**	-0.002	-0.049*	0.869
	(-0.55)	(42.74)	(2.68)	(7.47)	(5.98)	(-0.04)	(-2.42)	
1	**-0.278***	1.070**	0.095*	0.334**	0.037	0.023	-0.006	0.842
	(-2.52)	(37.83)	(2.51)	(6.05)	(0.74)	(0.31)	(-0.22)	
2	**-0.324****	1.073**	0.022	0.198**	0.239**	0.107	-0.067*	0.822
	(-2.72)	(35.17)	(0.53)	(3.33)	(4.44)	(1.33)	(-2.49)	
3	**-0.041**	1.075**	0.007	0.087	-0.062	0.029	-0.134**	0.849
	(-0.35)	(35.50)	(0.17)	(1.47)	(-1.16)	(0.37)	(-4.99)	
4	**0.197***	0.983**	-0.201**	-0.300**	-0.080+	0.175**	-0.186**	0.903
	(2.11)	(41.06)	(-6.28)	(-6.42)	(-1.88)	(2.78)	(-8.80)	