Received: 24 November 2022 | Revised: 22 April 2025 | Accepted: 11 May 2025

DOI: 10.1002/smj.3726

RESEARCH ARTICLE

SMS | Strategic Management Journal

WILEY

Investors' attention and the paradox of technologically related diversification: Evidence of stock market mispricing

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Abstract

Research Summary: We show that multi-business firms pursuing technologically related diversification often face a paradox. While such strategies can yield superior financial performance through technological synergies, investors with limited attention tend to undervalue them due to their complexity. Using asset pricing methods, we find that these firms consistently outperform market expectations. The degree of mispricing depends on investor attention and the availability of information needed to assess the strategy's value. Our findings highlight how informational frictions can distort market valuations of complex corporate strategies.

Managerial Summary: Firms diversifying across technologically related businesses may unlock significant value through synergies—but this value is often missed by investors. The complexity of these strategies challenges investor understanding, leading to market undervaluation. We find that improving how firms communicate their technological capabilities—such as using clearer, more familiar language in patent disclosures—can enhance investor recognition and improve market valuations.

KEYWORDS

abnormal returns, investors' attention, patents, stock market anomaly, technologically related diversification

1 | INTRODUCTION

Over the span of more than a century, DuPont Corporation has developed a multi-billion dollar product diversification strategy rooted in science and technology. The company's expertise in discovering and commercializing innovative technologies and materials, exemplified by breakthroughs such as Nylon, Teflon, and Kevlar, has sustained its competitive presence across multiple industries, including chemicals, agriculture, electronics, communications, bioscience, and nutrition. This strategy is encapsulated in the corporate slogan: "The Miracles of Science."

However, in 2014, this comprehensive product diversification approach faced significant criticism from analysts and investors. BGC Partners equity analyst Mark Gulley dismissed DuPont as a "conglomerate, a grab bag of unrelated businesses."[1] Reflecting this sentiment, activist investor Nelson Peltz led a campaign advocating for the division of DuPont into three independent entities, proposing the complete elimination of central research. At that time, the research division operated on an annual budget of just $220 million (0.7% of company sales).[2] DuPont's top management contested these initiatives, arguing that analysts and investors failed to appreciate the spillovers and long-term benefits associated with investing in overarching technology, which could yield advantages over 10–20 years. Regardless of who was correct in the DuPont case, a broader question persists: how effectively does the stock market anticipate the benefits arising from technological synergies?

A more recent example involves Zomato, a food delivery and restaurant discovery platform, acquiring Blinkit, an instant grocery delivery service, and Hyperpure, a B2B platform for fresh restaurant supplies, as part of its strategy to leverage technological synergies. During the Q4 2022 earnings call, Zomato executive Akshant Goyal explained, "It is an integrated tech. It is an integrated CRM. It is an integrated delivery fleet." He elaborated that their technological infrastructure allows cross-selling between Zomato's large customer base on food delivery and the quick commerce segment while also improving operational efficiency through a shared delivery fleet. Despite these efforts, analysts initially doubted the effectiveness of the synergies, questioning the operational differences between food delivery and quick commerce logistics. In July 2022, Zomato shares tumbled over 20% following the announcement of the Blinkit acquisition. However, from that low point to the end of 2024, the stock surged fivefold, driven largely by the strong operational performance of the acquired businesses.[3]

[1]The complete quote is in https://www.institutionalinvestor.com/article/2bsup25m3wdeka2j3vchs/portfolio/former-chemical-giant-dupont-attempts-to-reinvent-itself-once-more.

[2]From https://billgeorge.org/blog/the-dupont-proxy-contest-is-a-battle-for-the-soul-of-american-capitalism.

[3]https://www.reuters.com/markets/asia/indias-zomato-surges-9-after-q1-profit-beat-2024-08-02/ and https://www.livemint.com/market/stock-market-news/zomato-shares-tumble-over-20-after-announcement-of-blinkit-acquisition-11656913193298.html?utm_source=chatgpt.com.

In this article, we argue and demonstrate that the stock market mispricing of technologically related diversification (TRD) strategies is widespread and common. It is important to clarify that we do not claim TRD strategies always result in superior firm financial performance. Existing literature acknowledges that related diversification strategies often entail increased coordination costs, and TRD can only yield superior performance when the synergy benefits outweigh these coordination costs (Zhou, 2011). Therefore, TRD can create value for certain companies while proving detrimental for others. Our argument is that the stock market consistently undervalues the future benefits associated with TRD for firms adopting this strategy.

Our investigation is motivated by the stock market's apparent difficulties in properly evaluating the consequences of firm actions, particularly those involving technology, leading to a mismatch between expected and realized performance (e.g., Benner, 2010; Cohen et al., 2013; Litov et al., 2012; Oehmichen et al., 2021; Sloan, 1996). From a strategic management perspective, this issue is significant. Stock performance influences key strategic outcomes such as executive compensation and turnover (Bushman et al., 2010; Jenter & Kanaan, 2015), mergers and acquisitions, and corporate investment (Polk & Sapienza, 2009). If the stock market fails to fully incorporate the long-term consequences of TRD strategies into current prices, firm management faces a dilemma: either pursue value-creating strategies that the stock market does not appreciate in the short term or choose actions that are easier for external investors to evaluate but generate lower long-term returns (Myers & Majluf, 1984).

To understand the market's assessment of TRD, prior studies have examined valuation levels using market capitalization or market multiples, finding that related diversifiers enjoy higher valuations than unrelated ones (e.g., Berger & Ofek, 1995; Miller, 2006). While valuable, these analyses provide a *static* picture and are typically agnostic about whether these valuation levels represent *market efficiency*. That is, they show how TRD firms are valued relative to others, but not whether that valuation fully and promptly incorporates all available information about the future prospects of their TRD strategy.

Our study takes a different approach, grounded in asset pricing theory, to directly assess market efficiency concerning TRD. We focus on *return predictability*. According to the efficient market hypothesis (EMH), if markets are efficient, current stock prices should reflect all publicly available information, making future returns unpredictable based solely on that past information (Fama, 1970). Therefore, if a firm characteristic derived from public, historical data at time t (like our measure of TRD) consistently predicts abnormal stock returns at time $t+1$, it implies that the market price at time t did not fully reflect the information embedded in that characteristic. In this context of return predictability, such a finding suggests *mispricing*—specifically, an undervaluation if the predictable abnormal returns are positive.

Thus, our core argument is that if TRD strategies are systematically undervalued, this should manifest as predictable positive future abnormal returns for firms pursuing them. By employing standard asset pricing methodologies focused on return predictability—specifically, portfolio regressions—we can test this directly. This approach allows us to move beyond static valuation comparisons and probe the dynamic efficiency of the market in pricing TRD strategies. Our finding that portfolios of high-TRD firms on average generate positive abnormal returns of 3.17% per year using value-weighted returns and 5.25% using equally weighted returns, after controlling for known risk factors, provides evidence consistent with the idea that the market does not fully incorporate the value implications of TRD ex ante, based on the public information available at the time.

We propose that forecasting the impact of TRD synergies on future cash flows imposes a significant information burden on investors, primarily due to the inherent complexity involved in evaluating such strategies, especially given investors' limited attention constraints. As detailed in our theory section, this complexity stems from two key sources: (1) the well-documented difficulty market participants face in pricing the financial implications of complex firm innovation strategies (Benner, 2010; Hirshleifer et al., 2018; Lee et al., 2019), and (2) the added challenge of evaluating technological synergies, which are often tacit, difficult to define precisely, and require deep technical knowledge often unavailable to external investors (Collis & Montgomery, 2009; Markides & Williamson, 1996). It is this fundamental complexity of assessing technological synergies under limited attention that we argue drives the systematic undervaluation of TRD.

While the inherent complexity of evaluating TRD synergies under limited investor attention forms our core mechanism, we acknowledge that characteristics such as the uniqueness or novelty of a firm's specific TRD strategy can further exacerbate these evaluation challenges, thus acting as important boundary conditions. For instance, we observe that the diversification strategies in our sample are often unique; 76% of the observations have no competitors operating in any of their 4-digit SIC combination. This uniqueness limits investors' ability to find benchmarks for comparison, assess performance, and infer potential synergies (Eaton et al., 2022; Gompers et al., 2016; Young & Zeng, 2015), thereby compounding the difficulty of evaluating an already complex strategy. Consistently, an analysis splitting the sample based on strategic uniqueness reveals two key insights. First, it shows that the mispricing of TRD firms is concentrated among those pursuing unique strategies, highlighting uniqueness as a condition exacerbating evaluation complexity. Second, within this unique subsample—where any common valuation effects associated with uniqueness itself should be captured by fixed effects or the intercept—we find that the positive association between TRD and subsequent abnormal returns persists, even when controlling for technological novelty. This latter finding strongly suggests that the complexity inherent in evaluating TRD provides an independent source of mispricing, separate from the difficulties posed by uniqueness or novelty alone, although these factors often co-occur and potentially amplify the challenge.

We investigate several factors expected to mitigate the undervaluation by reducing information asymmetries or complexity. We examine the roles of investor attention, analyst coverage, the increased transparency following the American Inventor's Protection Act (AIPA), and technology familiarity. Consistent with our hypothesis, we find evidence suggesting these factors act as negative moderators, weakening the link between TRD and subsequent abnormal returns (alpha). However, these moderator analyses have nuances: the AIPA analysis faces challenges regarding the parallel trend assumption, and for investor attention, its meaningful association with alpha emerges primarily when considered alongside the other moderators in a comprehensive model. Despite these specific limitations and our caution against making causal claims, the overall pattern across these moderators lends support to our core argument that difficulties in information processing drive the mispricing of TRD.

This study contributes to the literature on TRD by demonstrating that the value of TRD strategies is not fully reflected in the stock market prices of TRD firms. Previous research has examined the stock market performance of related diversifiers using market multiples, showing they benefit from higher valuations (Berger & Ofek, 1995; Miller, 2006). In the Supporting Information, we replicate these analyses using our novel measure of technology-based product diversification derived from cross-patent citations. However, while earlier studies suggest that related diversification generally outperforms unrelated strategies in stock market performance, our findings suggest that TRD firms still fall short of having their full value recognized by investors.

Furthermore, we emphasize the critical role of limited investor attention in assessing complex firm strategies (Bushee, 2001; Hirshleifer et al., 2018). By examining technological familiarity (i.e., the opposite of technological novelty), our study expands on the literature related to market coverage and the misvaluation of firm strategies (Litov et al., 2012; Oehmichen et al., 2021). This body of work highlights a paradox where firms must choose between creating value through unique, novel strategies and having that value adequately recognized by market participants. Our results indicate that this dynamic also applies to TRD strategies. However, our findings extend beyond prior evidence of difficulties in evaluating novel strategies, as the mispricing of TRD persists even when controlling for patent novelty. While the effect of TRD mispricing is independent of technological novelty, we find that novelty further complicates the assessment of TRD synergies.

Together, our findings underscore the paradox managers face in contexts of asymmetric information between firms and investors. Managers must choose between strategies that create long-term value but are poorly understood by the market and strategies with lower long-term value creation potential but stronger short-term market recognition.

2 | ANALYTICAL FRAMEWORK: THE DIFFICULTIES IN EVALUATING TECHNOLOGICAL SYNERGIES

We analyze whether the stock market accurately prices technological synergies and how the release of information impacts this valuation. Following Sirower (1999), we define synergies as "increases in competitiveness and resulting cash flows beyond what the two companies are expected to accomplish independently." In our context, we expect technological synergies to occur because sharing or redeploying technological resources within firm boundaries creates economies of scale and scope. According to the resource-based view, leveraging common technological resources can enhance a firm's competitive advantage, as it may generate both operational and managerial synergies (Krishnan et al., 2009).

Operational synergies arise when sharing common technology reduces unit production costs, since technological knowledge is a scale-free asset that can be used repeatedly without incurring additional costs (Chatterjee, 1986; Wu et al., 2014). Furthermore, cross-product knowledge spillovers can lower costs as knowledge is transferred across different business units (Henderson & Cockburn, 1994; Martin & Eisenhardt, 2003).

Managerial synergies emerge because shared core technological competencies enable managers to organize internal markets for talent, capital, and machinery more efficiently than the external market (Farjoun, 1998; Gupta & Govindarajan, 1991; Martin & Eisenhardt, 2003). As a result, firms can share both knowledge-based and physical resources, which are easier to reconfigure internally than through external market reallocation mechanisms (Giarratana & Santalo, 2020).

However, TRD does not only bring synergies. The strategic management literature acknowledges that firms face significant coordination costs when pursuing these synergies (Aggarwal & Wu, 2015; Zhou, 2011; Zhou & Wan, 2017). Synergies create interdependencies that result in coordination costs. The more business units share inputs, the greater the coordination required. These coordination costs can manifest as intraproduct or interproduct coordination costs (Aggarwal & Wu, 2015). In our context, using the same technology to sell different products to the same customer incurs interproduct coordination costs, while using the same technology to customize products for distinct customers incurs intraproduct coordination costs.

Two specific sources of coordination costs arise when business units within the same firm share technology. Kotha et al. (2013) identify technology commercialization as a joint production effort requiring multiple specialists to coordinate their efforts. According to these authors, coordination costs arise from the need to synchronize efforts across inventor-commercial units and within each unit to collaborate on refining and modifying technology for commercialization. The inventor unit and the unit utilizing the technology must collaborate to understand its overall commercial value. Within-team coordination costs occur as units from different disciplines work together to integrate knowledge and develop working prototypes.

A second specific source of coordination costs arises when business units within the same firm share technology and need to coordinate knowledge across domains to manage interdependencies among specialists and generate new knowledge (Ben-Menahem et al., 2016). This coordination may require both formal and informal structures.

Overall, these arguments suggest that a TRD strategy enhances firm profitability only when the value of synergies exceeds the increase in coordination costs (Rawley, 2010; Zhou, 2011).[4] We do not claim that the value of synergies will always outweigh coordination costs; indeed, for some firms, TRD may erode value. However, we presume that firms for which the value of synergies exceeds corresponding coordination costs are more likely to pursue a TRD strategy. In other words, while the average effect of TRD may be neutral or negative across all companies, we anticipate a positive correlation between TRD and financial performance, driven by firms with net positive synergies self-selecting into such strategies.

Our main thesis is that the synergies that characterize TRD are unlikely to be properly priced by the stock market due to limited investor attention, which creates challenges when evaluating complex strategies. Two factors contribute to the complexity of TRD strategies: (1) the difficulty of evaluating the value of technology itself, and (2) the complexity of evaluating technological synergies. We address each factor below.

Previous literature has provided ample evidence of the difficulties market participants face in properly pricing the financial implications of complex firm innovation strategies. Benner (2010) examines the emergence of two new technologies—digital photography and wireline telecommunications—and demonstrates how analysts often overlook firm strategies that incorporate these innovations. Hirshleifer et al. (2018) find that firms with greater innovation originality are undervalued. Innovation originality, measured by the number of technological classes cited in firm patents, predicts both higher, more stable profitability and higher abnormal stock returns. These ex-post abnormal returns suggest that the stock market had undervalued firms with higher levels of innovation originality before the innovations were fully recognized. Similarly, Lee et al. (2019) show that the returns of technology-linked firms predict the stock market returns of focal firms. This finding implies that investors fail to anticipate the impact of one firm's higher (or lower) performance on other firms utilizing the same technology. Overall, these results indicate that market participants struggle to incorporate the financial consequences of technological activities into stock market prices.

In addition to these challenges in evaluating the financial implications of technology, investors face an additional burden when assessing synergies linked to the use of shared technological knowledge. Synergy itself is an elusive concept, difficult to define and measure. If firms,

[4]There are other reasons that may explain why firms engage in distinct types of product diversification strategies. Agency problems and managerial self-interest can drive firms to undertake diversification strategies (Amihud & Lev, 1981). However, in our context, we focus on the empirical implications of value-creating diversification strategies while controlling for alternative explanations in our empirical setup.

with access to inside information, struggle to evaluate synergies in an M&A context, investors with limited attention and no insider knowledge face even greater difficulties (Collis & Montgomery, 2009; Markides & Williamson, 1996).

Two main reasons explain why investors struggle to price the financial implications of technological synergies. First, the amount of technical knowledge required to properly evaluate technological synergies is likely greater for external investors than for firm insiders. Investors do not have access to proprietary information that companies withhold for fear of appropriation (Arrow, 1962). Moreover, investors are rarely specialized in any one company, and their investment strategies typically span multiple companies and industries. As a result, it is harder for them to acquire the necessary information to anticipate the value creation potential of synergies, especially when attention is a limited resource. Second, technological synergies are embedded in tacit knowledge (as opposed to codified knowledge). As Nonaka (1994) explains: "Without some form of shared experience, it is extremely difficult for people to share each other's thinking processes. The mere transfer of information will often make little sense if it is abstracted from embedded emotions and nuanced contexts that are associated with shared experiences." This shared experience requires socialization, and socializing with external investors is inherently more challenging. Without access to tacit knowledge, it becomes more difficult for investors to assess technological synergies.

In summary, we have outlined why investors may find it complex to evaluate technological synergies, and why this complexity is compounded when trying to price their value. Consequently, the positive impact of technological synergies on firm performance may come as a surprise to investors who have limited attention to evaluate such complex strategies. Therefore, we hypothesize:

Hypothesis 1. Firms following a TRD strategy will tend to be under-valued by the stock market.

2.1 | TRD and market efficiency

Understanding how the stock market assesses complex strategies like TRD is crucial for strategic management. Prior research often examines valuation levels, for instance, using market capitalization or market multiples, and finds that related diversifiers can command higher valuations than unrelated ones (e.g., Berger & Ofek, 1995; Miller, 2006). While informative, these studies provide a static snapshot. They tell us how TRD firms are valued relative to others at a point in time, but they do not directly address whether this valuation accurately reflects all available information or if the market efficiently anticipates the future performance implications stemming from the TRD strategy. In essence, a high valuation multiple does not necessarily mean the market fully understands or correctly prices the underlying strategic synergies.

Our study adopts a different lens, drawing from asset pricing theory in finance, to directly probe the dynamic efficiency of the market concerning TRD. The core idea revolves around return predictability and its implications under the EMH. The EMH, particularly in its widely accepted "semi-strong" form, posits that current stock prices should already reflect all publicly available information (Fama, 1970). A key implication is that investors should not be able to systematically earn abnormal returns—that is, returns exceeding what's justified by the investment's risk—by trading solely on public information known today. If you could consistently predict future abnormal returns using only past public data (like a firm's TRD level last year), it would suggest the market is not fully efficient; it has not incorporated that information into today's price correctly.

Therefore, our approach tests whether a firm characteristic derived from public, historical data at time t (specifically, our measure of TRD) consistently predicts abnormal stock returns at time $t+1$. Finding such predictability suggests that the market price at time t did not fully impound the information embedded in the TRD characteristic. Within this framework, consistent predictability of positive abnormal returns implies mispricing—specifically, that the market systematically undervalues firms with high TRD, only recognizing the benefits later through higher-than-expected returns.

While the EMH serves as a vital benchmark, finance research acknowledges that real-world markets are not perfectly efficient. Numerous "anomalies"—patterns where specific characteristics predict future abnormal returns—have been documented, even in sophisticated markets (Carhart, 1997; De Bondt & Thaler, 1985; Jegadeesh & Titman, 2001; Sloan, 1996; Summers, 1986). We argue that the inherent complexity of evaluating TRD strategies, particularly the subtle, long-term nature of technological synergies and the limited attention of investors, makes TRD a prime candidate for such mispricing. Unlike more overt market patterns, the difficulty in assessing TRD may prevent investors from quickly identifying and trading on the undervaluation, allowing it to persist.

Thus, by focusing on return predictability, we move beyond static valuation questions to directly test whether the market efficiently incorporates the strategic value proposition of TRD. This asset pricing approach allows us to investigate if there is a systematic gap between the value potentially created by TRD strategies and how that value is recognized and priced by investors over time.

3 | MEASURING TRD

Our proxy for TRD is constructed by combining patent data from the National Bureau of Economic Research (NBER) patent database (Hall et al., 2001) with information on firms' operating sectors from the Standard & Poor's Compustat Segment database. This measure can only be calculated for diversified firms, defined as those that report sales in more than one SIC4 industry within a given year. It is available for the period 1980–2006, constrained by the availability of patent data in the NBER database and by our use of a rolling 5-year window to calculate the measure.

Specifically, TRD is a cross-citation measure designed to capture whether a firm's operating sectors exhibit significant technological interactions. Citations in patents indicate the relevant prior art upon which innovations are based (e.g., Katila & Ahuja, 2002; Morandi Stagni et al., 2021; Sorensen & Stuart, 2000). Based on this premise, we argue that by examining the operating sectors of the citing and cited patent owners, we can construct an industry-level map of technological interactions. The greater the number of citations between a sector pair, the higher the overlap between the two sectors' knowledge bases, and consequently, the greater the potential benefit a firm can gain by combining them within its portfolio of businesses.

Cross-citation measures are not new and have been widely used to capture inter-organizational knowledge flows (Ellison et al., 2010; Mowery et al., 1996; Schildt et al., 2012). Our measure follows a similar logic but focuses on intra-organizational knowledge sharing between the units of a diversified firm. In this respect, our approach is akin to that of Morandi

Stagni et al. (2020), with the distinction that we calculate a unique TRD value at the firm level using sector cross-citations, while their method estimates the relatedness of a business unit to its parent firm. Our measure also shares similarities with Neffke and Henning's (2013) relatedness proxy. While they use cross-industry labor flows to assess skill-relatedness, we utilize patent citations to capture knowledge flows across industries.

Using the NBER patent citation data file, we calculate firms' TRD by first assigning both citing and cited patents to industries based on the operating 4-digit SIC of the patent owners.[5] Then, we compute a 5-year rolling sum of total cross-citations between each industry pair, as follows:

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

where $CrossCit_{\mathrm{A,B},t}$ is the total cross-citation between a Sector A–Sector B pair in year t; $C_{\mathrm{A}\rightarrow\mathrm{B}}$ is the total number of times that patents granted in a given year to companies operating in SIC Sector A cite patents granted to companies operating in SIC Sector B; and $C_{\mathrm{B}\rightarrow\mathrm{A}}$ is the opposite. With these sums, we determine the TRD for each diversified firm in our sample by first averaging cross-citations between operating industries, and by then taking the natural logarithm of the value obtained. Formally:

$$\mathrm{TRD}_{i,t} = \ln\left(1 + \sum_{X=1}^{N}\sum_{Y=X+1}^{N} CrossCit_{X,Y,t} * \frac{s_{i,X,Y,t}}{\sum_{X=1}^{N}\sum_{Y=X+1}^{N} s_{i,X,Y,t}}\right), \tag{2}$$

where $\mathrm{TRD}_{i,t}$ is the estimate of firm i's technological relatedness in year t; N are the sectors in which a diversified firm operates; and $s_{i,X,Y,t}$ is the sum of sales of operating segments X and Y for firm i in year t.

Previous research has operationalized technological relatedness in terms of the applicability of a firm's patent portfolio to different sectors (Miller, 2006; Silverman, 1999). For instance, Silverman (1999) uses a mapping of patent classes to economic sectors to calculate a proxy for the "fit" between a firm's patent portfolio and a sector that represents a potential diversification target. We believe that Silverman's (1999) approach is close to optimal in its application. However, we argue that calculating a measure of fit between a firm's patent portfolio and its current operating sectors does not adequately capture the potential for technological synergies across two distinct industries. We highlight three main issues.

[5]We exclude self-citations, and we weight patents equally in the calculation of TRD. In the case of patents with multiple owners operating in different SIC codes, we divide the total weight of the patent equally across different SIC codes. If patents are owned by diversified firms, we divide the weight of the patent between the different SIC codes according to the proportion of segment sales. A potential alternative would be that of using only the patents of single segment firms to improve the accuracy in sector attribution. Unfortunately, for an important number of SIC sectors diversified firms are the main firms patenting. We thus believe that by excluding diversified firms from the calculation we might in many cases underestimate the potential for synergies across sectors. Nevertheless, in the Supporting Information we test the robustness of our analyses to the use of a TRD proxy calculated on single segment firms only. We obtain similar results.

First, patent classes are not defined independently of economic sectors; instead, there is a significant overlap between the two (Morandi Stagni et al., 2021). If the sector of usage influences the classification of technology, then using patent classes to assess the relatedness of sectors may not be much better than using SIC codes. Second, a relatively high fit does not necessarily imply that the sectors share technology. It could simply result from a firm patenting in the primary technological classes of the sectors in which it operates, which does not necessarily indicate that the sectors are technologically related. Third, firms operating in low-tech sectors often exhibit extreme levels of technological fit. This occurs because the fit of a patent class to a sector is calculated as the ratio of the number of patents in the class assigned to firms operating in that sector, divided by the total number of patents in the class. In very active patent classes, full overlap between the class and a sector is rare; however, in less active patent classes, it is more common due to issues related to small sample sizes. Consequently, calculating relatedness as the average "fit" of the patent portfolio may lead to paradoxical results. Despite these limitations, we replicate our baseline analyses using the Silverman measure and find qualitatively similar results.[6]

In comparison to this alternative approach, our measure, which is based on citation flows, directly captures whether two sectors can provide each other with valuable knowledge inputs for innovation, thereby more effectively tapping into the definition of synergy. Its primary limitation is that our sector-level methodology may be less accurate in capturing unique and exceptional proprietary technologies held by certain firms in our sample. However, we argue that examining sector-level interactions offers several advantages. First, the procedure the NBER uses to match companies with patents is not perfect, and in some cases, firms may own patents but be flagged as non-matches in the database (Hall et al., 2001), leading to an underestimation of their technological capabilities. By calculating relatedness at the sector level, we mitigate this issue. Second, not all innovations are patented; a lack of patents does not equate to a lack of valuable proprietary technology. Companies often seek patent protection only for a fraction of their most significant innovations (Fontana et al., 2013). Third, the absence of proprietary technology does not necessarily prevent a company from benefiting from operating in sectors that share a similar technological base. Firms can exploit economies of scope through in-licensing technology. Additionally, both machinery and human resources are arguably more fungible across technologically related sectors, meaning technological relatedness is linked to benefits from internal redeployment. Lastly, focusing on sector-level technological interactions helps address the potential criticism that our results might stem from firms' stock of technology, rather than from technological synergies across a firm's sector portfolio.

Our TRD measure captures knowledge flows across industries using patent citations. While investors have access to patent information, and substantial evidence suggests they utilize it in their investment decisions (Martens, 2023), we argue that they may struggle to accurately price technological synergies, even when cross-industry patent citations are observable. Patent citations highlight potential technological synergies, but identifying and quantifying these synergies in practice is challenging. Investors may find it difficult to assess the economic implications of these citations due to the complexity and uncertainty involved in translating shared technological knowledge into concrete financial outcomes. As a result, the market may underprice these synergies despite their presence in the patent data.

[6]These analyses are available upon request.

In Table 1, we present summary information regarding how firms and sectors relate to our TRD proxy for the years 1980, 1990, and 2000. The right section of the table lists the five sector pairs with the highest levels of relatedness for each year. For example, in 2000, one of the strongest linkages occurs between the photographic industry and the sector producing peripheral equipment for computers, likely due to the expanding market for digital cameras during that period. Interestingly, just 10 years earlier, the photographic supply sector and the chemical industry were highly related, probably because of photographic film technology. Overall, Table 1 demonstrates that over the span of our sample, there has been significant turnover in the highest relatedness sector pairs and firms. Chemical and cosmetic firms dominated the list in 1980, while electronics firms and sectors were at the top in 2000. In 1980, Carter Wallace ranked second for TRD in our sample. The firm was active in both cosmetics, with products like Arrid deodorant and Nair depilatory cream, and pharmaceuticals, with drugs such as the antianxiolytic Miltown and the painkiller Soma. By 2000, we observe semiconductor companies like JDS Uniphase, and firms combining SICs 3841 ("Surgical and Medical Instruments and Apparatus") and 3845 ("Electromedical and Electrotherapeutic Apparatus"), resulting from diversification efforts aimed at meeting needs in specific therapeutic areas. For instance, Datascope, which produces medical devices for cardiac patients, pioneered intra-aortic balloon pump systems and catheter technology. By the late 1990s, Datascope operated four distinct divisions, all focused on treating cardiovascular conditions: Cardiac Assist developed and manufactured intra-aortic balloon pumps and catheters; Patient Monitoring created devices to measure vital patient data (e.g., cardiac output, blood pressure, temperature, and blood oxygen saturation); Collagen Products marketed a VasoSeal line of arterial sealant devices; and InterVascular produced knitted and woven polyester-coated grafts to replace diseased arteries.

A potential concern with our measure is that, as shown in Table 1, the level of relatedness among high TRD firms increased over time, from 4.22 in 1980 to 9.29 in 2000. This trend results from our decision to consider both sector technological intensity and technological overlap in calculating TRD. Patent activity grew consistently over the sample period, partly due to economic development and rising R&D investments, and partly due to the increasing significance of the electronics industry, which is known for its high patent intensity. We argue that accounting for technological intensity in the measure is necessary to test our theory, as the potential for technological synergies inevitably grows with the importance of technology in a sector pair. Additionally, considering only technological overlap would yield paradoxical results, where sector pairs in low-tech industries are classified as highly related because the few patents granted in those sectors show concentrated citations. Despite these arguments, we also conduct analyses using sector-adjusted market returns as in Berger and Ofek (1995), which rule out the concern that our findings are driven by technological differences across sectors. These results confirm that the positive effect of synergies arises from both the technological importance of a sector pair and the overlap in their knowledge bases.

Regarding our baseline TRD measure, we acknowledge that if the same sector pairs consistently appear as the most related, the proxy might lack sufficient heterogeneity to allow for a meaningful test of the theory. While the high turnover in top TRD sectors, as reported in Table 1, should alleviate some of these concerns, we plot the relatedness trajectory of the top sector pairs from 1990 in Figure 1. As shown, all the sectors considered peaked in relatedness relative to other sectors in 1990 and experienced a decline afterward. Aside from these considerations, we note that all our analyses include specific controls and fixed effects to separate the baseline effect of technology on performance from that specifically due to synergies.

TABLE 1 Top five TRD firms and sector pairs in 1980, 1990, and 2000.

Firm	Main sector	TRD	Sector 1	Sector 2	TRD
1980					
Witco	2869—Chemicals	4.22	4812—Radiotelephone Communications	3661—Telephone and Telegraph Apparatus	4.79
Carter Wallace	2844—Cosmetics	4.09	2911—Petroleum Refining	2869—Industrial Organic Chemicals, NEC	4.22
Motorola	3663—Telephone Apparatus	4.04	2834—Pharmaceutical Preparations	2844—Perfumes and Cosmetics	4.09
Deere & Co.	3523—Farm Machinery	3.90	3663—Radio and Television Broadcasting	4812—Radiotelephone Communications	4.09
Total Petroleum	2911—Petroleum	3.88	3674—Semiconductors and Related Devices	4812—Radiotelephone Communications	4.08
1990					
Block Drug	2834—Pharmaceutical	6.04	3861—Photographic Equipment and Supplies	3651—Household Audio and Video Equipment	7.03
Schering-Plow	2834—Pharmaceutical	6.04	2911—Petroleum Refining	2869—Industrial Organic Chemicals, NEC	6.79
Chrysler	3711—Motor Vehicles	6.02	3711—Motor Vehicles and Passenger Car Bodies	3714—Motor Vehicle Parts and Accessories	6.65
Ford Motor	3711—Motor Vehicles	6.02	2869—Industrial Organic Chemicals, NEC	3861—Photographic Equipment and Supplies	6.60
Mobil	2911—Petroleum	6.01	2911—Petroleum Refining	2821—Plastics Materials	6.52
2000					
JDS Uniphase Corp	3674—Semiconductors	9.29	3674—Semiconductors and Related Devices	3571—Electronic Computers	9.54
Datascope Corp	3845—Electromedical	8.61	3663—Radio and Television Broadcasting	3674—Semiconductors and Related Devices	9.29
Technicolor Sa	7812—Motion Picture	8.59	3861—Photographic Equipment and Supplies	3577—Computer Peripheral Equipment, NEC	8.95
Palm Inc	3571—Electronic Computers	8.46	3841—Surgical and Medical Instruments	2834—Pharmaceutical Preparations	8.79
Symmetricom Inc	3661—Telephone Apparatus	8.44	3661—Telephone and Telegraph Apparatus	4813—Telephone Communications	8.61

4 | RESULTS

4.1 | TRD and excess returns

Our primary tests for whether the stock market incorporates information about TRD in determining the value of firms' stocks involve portfolio regressions. The underlying idea is straightforward. The returns of a diversified stock portfolio are largely determined by the portfolio's exposure to a few key risk factors: the market risk premium (Sharpe, 1964), size and growth

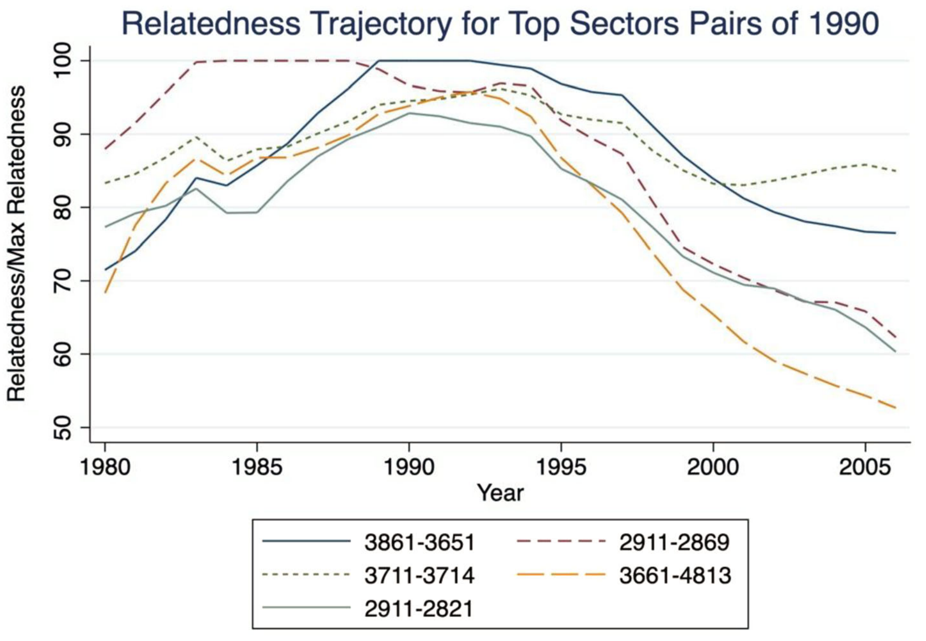

FIGURE 1 Relatedness trajectory for top sectors pairs of 1990.

factors (Fama & French, 1992), and a momentum factor (Carhart, 1997). These variables explain a significant portion of the time-series returns for the portfolio, making it difficult to identify excess returns (either positive or negative) that remain unexplained. A common strategy for testing the existence of an asset pricing anomaly associated with a variable involves forming portfolios based on quantiles of the anomaly variable. Each portfolio is then analyzed with a separate regression model, and the intercept (known as the alpha) from each model is evaluated to see if a pattern emerges. Specifically, if the alpha is positive, it indicates that the portfolio generates returns in excess of what could be expected based on its exposure to the known risk factors; conversely, a negative alpha implies the opposite.

Portfolio regressions have a long history in finance, with early studies by Black et al. (1972) and Fama and MacBeth (1973) being among the first to apply this method.[7] Blume (1970) articulated the original motivation for grouping stocks into portfolios as a way to reduce measurement errors. If the errors in variable measurements are not perfectly correlated across stocks, they tend to cancel each other out when the assets are grouped into portfolios. Thus, using portfolios as test assets allows for more efficient estimates of factor loadings. Blume (1970) argued that these more precise estimates of factor loadings also enable more accurate estimation of factor risk premia.

Our sample for the return test combines CRSP monthly data, Compustat, and NBER data. We begin with the universe of Compustat firms that reported sales in more than one 4-digit SIC

[7]A number of empirical studies use portfolio regression as the tests for whether the market incorporates publicly available information. For example, Gompers et al. (2003) form portfolios of stocks based on a firm-level measure of shareholders rights. They find that the stocks of firms that award more protection to shareholders tend to outperform their counterparts. Edmans (2011) instead evaluates the performance of a portfolio of the "100 Best Companies to Work For in America" and finds that the market does not fully incorporates information about employee satisfaction.

segment during the period from 1980 to 2006. We then match this sample of diversified firms with CRSP data, eliminating firms with missing year $t+1$ monthly returns or those with monthly returns based on the bid-ask spread average rather than actual transactions. For the test, we match TRD estimates for year t (calculated using patents granted between years t and $t-4$, and therefore publicly available) with the monthly returns of firms' securities in year $t+1$. This procedure helps avoid "look-ahead bias," which occurs when researchers use new (i.e., previously unknown) information to explain contemporaneous returns. Market reactions to new information are expected; pricing anomalies are defined by the ability to predict future returns based on information already publicly known. Our final sample includes 165,252 monthly returns from 1768 different diversified corporations, spanning the period from 1981 to 2007.

We divide the sample into six portfolios: one containing all diversified firms exhibiting a zero TRD value according to our proxy, and five based on the quintile distribution of TRD recalculated on December 31st of each year prior to the return. For example, the portfolios with returns from 1995 are based on the TRD distribution of firms in 1994. For each portfolio, we thus calculate an equal-weighted monthly return, as the simple average of the returns of each security in the portfolio, and a value-weighted monthly return, as the weighted average of the returns of each security, based on the market capitalization exhibited on December 31st of year $t-1$ relative to the rest of the stocks in the portfolio.[8] We choose to form six portfolios to strike a balance between two considerations. On one hand, increasing the number of portfolios allows for a more granular view of the relationship between TRD and returns. On the other hand, we need enough diversification in each portfolio to average out idiosyncratic risk. With this approach, our baseline portfolios contain an average of 86 securities each.

Our baseline test for mispricing associated with TRD is based on the Carhart (1997) four-factor model of performance attribution. Specifically, we regress the time-series returns of each portfolio on four risk factors. The general form of the regression is:

$$R_t = \alpha + \beta_1 * Market\ Risk\ Premium_t + \beta_2 * Size_t + \beta_3 * Value_t + \beta_4 * Momentum_t + \epsilon_t, \tag{3}$$

where R_t is the monthly return of the portfolio in excess of the 1-month T-bill; $Market\ Risk\ Premium_t$ is the premium associated with the market portfolio calculated in the same way; and $Size_t$ (small size minus big size), $Value_t$ (high book-to-market value minus low book-to-market value), and $Momentum_t$ (high momentum minus low momentum) are month t returns associated with zero-investment portfolios, which we use to capture the sensitivity of stock returns to size, book-to-market ratios, and past returns. Data on these factors come from the Wharton Research Data Service (WRDS). The intercept (α) of the model represents the abnormal monthly return realized by the portfolio after accounting for its exposure to the four sources of risk. We interpret a positive alpha (α) as evidence that the securities in the portfolio are undervalued given their level of risk, vice versa for a negative alpha.

Table 2 reports the results of the analysis, along with descriptive statistics for each portfolio. As shown, the average TRD level and the average market capitalization of the stocks increase linearly across portfolios. This observation reduces concerns that the alpha associated with high

[8]Value weighting returns provides advantages relative to equal weighting in case some of the portfolios end up being dominated by micro stocks, which command a liquidity premium. On the other hand, value weighted portfolios might also become unrepresentative if they contain a few mega caps with much higher market capitalization than the rest of firms.

TABLE 2 Portfolio analysis.

	Portfolios					
	0	**1**	**2**	**3**	**4**	**5**
Equal weighted returns						
Alpha	0.056	0.011	0.070	0.190	0.286	0.427
	(.595)	(.910)	(.513)	(.098)	(.013)	(.001)
Market risk premium	1.046	1.086	1.089	1.093	1.084	1.070
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Size	0.669	0.637	0.659	0.751	0.578	0.524
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Value	0.383	0.382	0.364	0.227	0.137	−0.161
	(.000)	(.000)	(.000)	(.000)	(.001)	(.000)
Momentum	−0.109	−0.103	−0.148	−0.199	−0.187	−0.205
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Observations	324	324	324	324	324	324
Adj. R-sq	0.875	0.890	0.883	0.882	0.876	0.876
Value-weighted returns						
Alpha	0.005	−0.284	−0.154	−0.068	−0.079	0.260
	(.967)	(.067)	(.214)	(.615)	(.555)	(.025)
Market risk premium	1.083	1.118	1.111	1.112	1.116	0.946
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Size	−0.054	0.115	0.061	−0.004	−0.047	−0.212
	(.189)	(.022)	(.126)	(.932)	(.278)	(.000)
Value	0.297	0.240	0.202	0.174	0.119	−0.361
	(.000)	(.000)	(.000)	(.001)	(.017)	(.000)
Momentum	−0.046	−0.017	−0.130	−0.129	−0.189	−0.192
	(.115)	(.633)	(.000)	(.000)	(.000)	(.000)
Observations	324	324	324	324	324	324
Adj. R-sq	0.801	0.754	0.832	0.804	0.817	0.859
Portfolios descriptive						
Number of stocks	101	87	86	86	86	86
TRD	0.00	0.13	0.80	1.95	3.36	5.50
Average MKT cap. (ml. $)	1588	2374	2469	3149	4197	10,410
Av. monthly ret. eq.	1.29%	1.27%	1.29%	1.32%	1.36%	1.33%
Av. monthly ret. val.	1.20%	0.94%	0.96%	1.03%	0.94%	0.94%

Note: Two-tailed p-values in parentheses below the coefficient. Each regression is estimated on the monthly returns of each portfolio of stocks between 1981 and 2007. Stocks are grouped into portfolios based on the prior year value of TRD. In particular, portfolio 0 includes all diversified firms exhibiting a zero value for TRD on December 31st of year $t-1$. Portfolios 1–5 are instead the results of the division into quintiles of the stocks of all diversified firms exhibiting a positive value of TRD at the same date. Equal-weighted returns represent the simple average of the monthly returns of the stocks in a portfolio. Value-weighted returns instead represent the weighted average of returns based on the market capitalization of stocks at December 31st of year $t-1$. We subtract the return of the 1-month treasury bill from the monthly returns of each portfolio. We regress the portfolio returns on the market risk premium, and on size, value, and momentum. These latter are the returns from zero investment portfolios designed to capture the sensitivity of our portfolios returns to these factors. Alpha is the estimate of interest and represents the intercept of each model.

TRD is due to liquidity issues. Furthermore, both the average equal-weighted and value-weighted monthly returns of the high TRD portfolio (1.33% and 0.94%, respectively) are comparable to those of the other portfolios. This highlights the difficulty in detecting the TRD anomaly by simply examining raw return data. The upper section of the table presents results for equal-weighted returns, while the lower section shows results for value-weighted returns. In both cases, the alpha for portfolio 5 is positive (coeff. = 0.427, $p = .001$ for equal-weighted; coeff. = 0.260, $p = .025$ for value-weighted), corresponding to annualized excess returns of approximately 5.25% and 3.17%, respectively.[9] Additionally, in both analyses, the alpha increases as TRD levels rise, with portfolios 3 and 4 exhibiting more positive alphas on average than the preceding portfolios.

Table 3 shows the results of a 5-year rolling window estimation of the alpha associated with the high TRD portfolio, testing whether the alphas linked to TRD are concentrated in specific periods of our sample. The results from this estimation are more variable, as each regression is based on only 60 monthly returns. Nonetheless, with one exception, the alpha remains consistently positive across the sample period for both equal-weighted and value-weighted returns. The size and significance of the effect also vary over time, with equal-weighted portfolios showing a higher concentration of abnormal profits at the beginning of the 2000s and value-weighted portfolios displaying stronger effects in the late 1980s and the second half of the 1990s.

Although portfolio regressions are a robust method for estimating the size and significance of the TRD misvaluation effect, this approach has two limitations: it does not test for moderators or include additional control variables. In Table 4, we adopt a different method to further test our theory and strengthen our findings. Specifically, we estimate an individual 3-year alpha for each firm using the same framework as in Equation (3). This means that, between 1981 and 2007, we have up to nine estimation periods for each firm, starting with the 1981–1983 period and ending with 2005–2007.[10] Applying this procedure to the same sample of firms and returns used in the portfolio analysis, we obtain 4588 observations from 1522 unique firms. The slight reduction in observations is due to missing monthly returns for some firms, which are necessary to estimate a 3-year alpha.

Table 5 reports descriptive statistics for the OLS regressions in Table 4. Each regression includes firm and year fixed effects, clustered standard errors at the firm level, and controls for firm size, profitability, leverage, product-market competition, R&D investment, technology familiarity, and patent portfolio size. For size, we use the natural logarithm of either sales or assets. Leverage is the ratio of short- and long-term debt to total assets. The competition measure reflects a weighted average by segment sales of the Herfindahl index of concentration at the 4-digit SIC sector level. For technological intensity, we use both the ratio of R&D expenses to sales and the natural logarithm of the firm's patent portfolio (i.e., the cumulative sum of patents granted to the firm). If R&D data are missing, we substitute the firm's R&D intensity with the industry average and include a "missing R&D" dummy in our models to account for firms

[9]While these numbers might appear high at first glance, it is important to note that we are talking about excess risk-adjusted returns, not raw returns. It is therefore not uncommon for anomaly research to report numbers in the same range or even higher. For example, Hirshleifer et al. (2018) reports a 2.9% annualized excess return for their portfolio with high innovation originality. Edmans (2011) observes that a portfolio of companies included in Fortune's "100 Best Companies to Work For in America" delivers a persistent 3.5% abnormal return. Cohen and Lou (2012) find a staggering 15% annualized excess return for their monthly rebalanced portfolio of "complicated firms."

[10]In all the analyses reported in the paper, we use the raw alpha obtained from the individual regressions. In unreported tests, we corrected the alpha by either multiplying the coefficient by one minus the p-value or by dividing it by its standard error to control for the influence of outliers. All the results remain virtually unchanged.

TABLE 3 Rolling 5-year portfolios.

	Equal-weighted		Value-weighted	
Year	**Alpha**	***p*-value**	**Alpha**	***p*-value**
1985	−0.009	(.960)	−0.041	(.874)
1986	0.207	(.228)	−0.014	(.946)
1987	0.153	(.382)	0.158	(.334)
1988	0.155	(.397)	0.217	(.196)
1989	0.147	(.396)	0.281	(.074)
1990	0.282	(.132)	0.319	(.029)
1991	0.032	(.879)	0.185	(.203)
1992	0.071	(.742)	−0.099	(.599)
1993	0.328	(.143)	0.168	(.491)
1994	0.555	(.014)	0.310	(.189)
1995	0.208	(.415)	0.173	(.506)
1996	0.351	(.143)	0.339	(.178)
1997	0.202	(.435)	0.625	(.011)
1998	0.190	(.464)	0.486	(.030)
1999	0.279	(.297)	0.455	(.074)
2000	0.651	(.096)	0.160	(.679)
2001	1.005	(.009)	0.276	(.497)
2002	1.132	(.004)	0.188	(.633)
2003	1.171	(.003)	0.071	(.855)
2004	1.095	(.010)	0.328	(.389)
2005	0.583	(.064)	0.297	(.326)
2006	0.278	(.344)	0.229	(.339)
2007	0.190	(.433)	0.081	(.671)

Note: Two-tailed *p*-values in parenthesis next to the coefficient. Each yearly Alpha is the result of a rolling window estimation that includes the monthly returns of the high TRD portfolio (portfolio 5) and the years between t and $t-4$.

that do not report R&D expenses (Koh & Reeb, 2015). If patent data are missing, we assume the value to be zero. We proxy for technological familiarity using data from Arts et al. (2021), calculated as the average cosine similarity between the text of patents granted to the firm and the rest of the patents granted by the USPTO in the previous 5 years. Finally, we proxy for sector technological intensity using the weighted average by segment sales of the number of patents granted to firms operating in a given 4-digit SIC sector each year.

Model 1 tests the baseline effect of TRD. The coefficient is positive, as expected (coeff. = 0.153, $p = .009$), indicating that TRD mispricing persists even when using a different estimation method and including a range of controls. Specifically, a one standard deviation increase in TRD more than doubles the expected alpha.[11] This analysis also includes fixed effects, year

[11]The average Alpha and the standard deviation of TRD in our sample are respectively equal to 0.19 and 2.17. Therefore, the expected Alpha one TRD standard deviation above the mean is: $0.19 + 2.17 \times 0.153 = 0.52$.

TABLE 4 Firm-level alpha analysis.

							Div. strategy	
							Unique	Diffused
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TRD	0.153	0.132	0.209	0.314	−0.360	−0.134	0.197	0.076
	(.009)	(.043)	(.004)	(.000)	(.223)	(.670)	(.006)	(.466)
TRD × Investors' attention		−0.190				−0.328		
		(.280)				(.046)		
TRD × Analysts' coverage			−0.021			−0.013		
			(.027)			(.169)		
TRD × Pat. Familiarity				−5.656		−5.601		
				(.004)		(.005)		
TRD × Time-to-Grant × Post AIPA					−0.029	−0.027		
					(.005)	(.010)		
Investors' attention		3.017				3.470		
		(.000)				(.000)		
Analysts' coverage			0.030			0.059		
			(.435)			(.133)		
Patents Familiarity	−2.555	−2.053	−2.617	2.813	−2.926	2.686	−5.254	0.076
	(.477)	(.566)	(.466)	(.462)	(.412)	(.483)	(.260)	(.466)
TRD × Time-to-Grant					0.021	0.019		
					(.049)	(.075)		
TRD × Post-AIPA					0.733	0.643		
					(.016)	(.034)		
Time-to-Grant × Post-AIPA					−0.023	−0.028		
					(.443)	(.331)		
Post AIPA					2.061	2.344		
					(.025)	(.012)		
Time-to-Grant					0.009	0.007		
					(.707)	(.750)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4588	4588	4588	4588	4588	4588	3465	1123
Adj. *R*-sq	0.035	0.041	0.036	0.038	0.042	0.052	0.044	0.108

Note: Two-tailed *p*-values in parentheses below the coefficient. The dependent variable is the individual firm's Alpha, estimated using 3 years of monthly data. The first estimation period uses the data 1981–1983, the last 2005–2007, we thus have a maximum of nine estimates of Alpha for each firm in our sample. Investors' Attention is one minus the percentage of outstanding shares held by transient investors, as classified by Bushee (1998). Analysts' Coverage is the average number of analysts' forecasts about the current fiscal year EPS that are formulated each month. Patents Familiarity is the average cosine similarity of the firm's recent patents (in a 3 years window) to all other patents granted in the 5 years before the granting of the focal patent (Arts et al., 2021). Post AIPA is a dummy variable that takes the value of 1 starting from 2002. Time-to-Grant is the average lag in months from patent application to grant in the operating sectors of the firm. In Regressions 7 and 8 and we split the sample based on whether there are other listed firms diversifying across the same SIC codes. If there are no other firms, the diversification strategy is unique; otherwise, it is diffused.

TABLE 5 Firm-level alpha analysis descriptive statistics.

		Obs.	Mean	SD	P 25	P 50	P 75	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Firm alpha	4588	0.19	2.95	−0.91	0.16	1.27	1.00													
2	TRD	4588	1.83	2.17	0.04	0.83	3.22	.06	1.00												
3	Investors' attention	4588	−0.08	0.12	−0.11	−0.02	0.00	.00	−.16	1.00											
4	Analysts' coverage	4588	1.95	2.33	0.00	1.36	2.90	.02	.23	−.35	1.00										
5	Patents Familiarity	4588	0.02	0.02	0.00	0.03	0.04	.00	.18	−.12	.21	1.00									
6	Patents Time-to-Grant	4588	28.85	5.82	25.31	27.43	30.84	.02	.07	−.03	.03	−.10	1.00								
7	Assets (ln)	4588	6.69	2.00	5.24	6.62	8.03	−.02	.26	−.13	.46	.10	.02	1.00							
8	EBIT/sales	4588	0.05	0.33	0.04	0.08	0.13	−.05	−.05	−.03	.08	.01	−.04	.20	1.00						
9	Leverage	4588	0.56	0.21	0.43	0.56	0.68	−.03	−.09	.01	.04	.00	.00	.36	.07	1.00					
10	Competition (HHI)	4588	0.24	0.16	0.13	0.20	0.31	.00	−.23	−.05	−.04	.09	−.13	−.04	.02	.04	1.00				
11	R&D intensity	4588	0.24	2.81	0.01	0.02	0.05	−.01	−.02	−.02	.01	.00	.01	−.02	−.04	−.02	−.01	1.00			
12	Missing R&D	4588	0.34	0.47	0.00	0.00	1.00	−.03	−.36	.03	−.01	−.20	.02	.03	.09	.12	−.03	.09	1.00		
13	Patent portfolio (ln)	4588	3.03	2.31	1.10	2.71	4.60	.00	.18	−.12	.21	1.00	−.10	.10	.01	.00	.09	.00	−.20	1.00	
14	Sector patents (ln)	4588	3.96	1.96	2.57	4.03	5.35	.01	.42	−.10	.34	.48	−.17	.46	.06	.09	.06	−.03	−.39	.48	1.00

dummies, and controls for technological intensity at both the firm and sector levels, as well as for the firm's technological familiarity. These results support our interpretation that the effect of TRD on mispricing is due to technological synergies, rather than technological intensity alone.

A straightforward question regarding our analysis is whether market participants could infer the benefits of a particular TRD strategy through simple indirect methods. For example, they might observe that firms often combine similar sets of SIC codes in their business portfolios. This question is relevant because investors and analysts typically value firms by comparing their performance to that of a set of "comparable corporations" (Eaton et al., 2022; Gompers et al., 2016; Young & Zeng, 2015). Comparable firms are used to estimate the cost of capital and growth rates for dividend-discount or cash-flow models, or to estimate a firm's total value based on multiples of measures like sales and earnings. Therefore, the availability of comparable firms directly influences market participants' ability to evaluate companies.

We therefore ask: How common is the diversification strategy of TRD firms among listed corporations? To answer this, we count how often specific pairs of SIC4 segments appear in the business portfolios of firms in the Compustat Segment universe in a given year. For example, in 2000, 21 firms operated simultaneously in SIC codes 1311 ("Petroleum and Natural Gas Extraction") and 2911 ("Petroleum Refining"). In contrast, only Ametek Inc. operated in both SIC codes 3823 ("Industrial Instruments for Measurement") and 3621 ("Motors and Generators") during the same year.

We then classify firms into two groups based on whether their diversification strategy is "unique" or "diffused." Firms with a unique diversification strategy have no competitors in the Compustat Segment universe exhibiting any of their sector combinations. Conversely, firms in the diffused group have at least one competitor with at least one of the same SIC4 sector pair combination. It turns out that 76% of the firms in our sample have a unique diversification strategy, meaning that no other firm in Compustat exhibits a similar combination of SIC4 segments. This uniqueness suggests that investors face challenges when trying to infer valuable synergies simply by examining firms' product-market diversification patterns.

In Models 7 and 8, we separate our observations based on whether the firm's diversification strategy is unique or diffused. We find a meaningful association between TRD and alpha only in Model 7, within the subsample of firms with a unique diversification strategy (coeff. $= 0.197$; $p = .006$).

While these tests targeting abnormal returns form the core of our empirical strategy for identifying potential mispricing, we supplement them with several complementary analyses detailed in the Supporting Information. These provide further context and robustness by examining: (1) the association between TRD and alternative outcomes like accounting performance and market multiples, and (2) market reactions within the specific context of Mergers & Acquisitions, comparing short-term announcement effects with long-term post-acquisition performance for TRD-related deals. These additional results consistently support our main conclusions.

Furthermore, also in the Supporting Information, we test an alternative explanation for our results. Recently, management scholars have pointed out that TRD may be linked to negative outcomes, such as increased coordination costs and the propagation of negative technological shocks across the organization (Chen et al., 2019; Rawley, 2010; Rawley & Simcoe, 2010; Shaver, 2006; Zhou, 2011). These arguments raise the possibility that our results may reflect TRD representing a risk factor considered by investors. To address this alternative explanation, we test the effect of our TRD proxy on direct measures of investment risk, such as the probability of bankruptcy and stock idiosyncratic volatility. We find no positive association between TRD and these variables.

4.2 | Testing the mechanism

In the theory section, we hypothesized that TRD mispricing stems from investors' limited attention, which causes difficulties in evaluating complex firm strategies. A direct implication of this hypothesis is that both the degree of attention investors and intermediaries devote to appraising TRD firms' stocks and the characteristics of the technological information environment surrounding TRD could influence the extent of mispricing.

To test the role of attention, we consider two moderators: investors' attention and stock market analysts' coverage. For investors' attention, we follow Hirshleifer et al. (2018) and use the inverse of the ownership percentage by transient investors as our proxy. This approach is motivated by empirical studies that show the presence of transient investors leads to an emphasis on short-term performance and an underweighting of long-term prospects (Bushee, 2001), making their presence among a firm's shareholders associated with abnormal returns (Yan & Zhang, 2009). For analyst coverage, we calculate the average monthly number of sell-side analysts' earnings-per-share (EPS) forecasts for the current fiscal year. Sell-side analysts, who work for brokerage houses, aim to reduce information asymmetry between firms and investors (e.g., Billett et al., 2017; Kelly & Ljungqvist, 2012). Their efforts stimulate trading and generate revenues in the form of trading commissions for the brokerage houses.

Models 2 and 3 in Table 4 report tests of these interactions in isolation, while Model 6 tests them together with the other moderators considered. As expected, both interactions are negative, supporting the idea that increased attention from stock market participants reduces the mispricing caused by TRD. Interestingly, the effect of analysts' coverage is more pronounced in Model 3, where the interaction is considered in isolation (coeff. = −0.021; p = .027), while the effect of investors' attention is stronger in Model 6 (coeff. = −0.328; p = .046), when tested together with the other moderators.

Next, we examine the characteristics of the information environment surrounding TRD by considering the technological information released by the firm and the patent system. We assess the complexity of the firm's disclosures by analyzing the wording of its granted patents, specifically focusing on the extent to which the language used is similar to that of other patents granted by the USPTO. The more standard (i.e., less novel) the language in the patent documents, the more familiar external parties should be with it. Naturally, we expect mispricing to decrease with greater familiarity in language, as familiarity should reduce external parties' cognitive burden when processing the information. To calculate a proxy for familiarity, we rely on data from Arts et al. (2021). After cleaning the patent text data, these authors estimate a cosine similarity measure for each patent, comparing its text with those of patents granted by the USPTO in the preceding 5 years. We use this measure to proxy Patents Familiarity as the average cosine similarity of patents granted to a firm over a 3-year rolling window from the focal year. We expect Patents Familiarity to capture how easily investors can understand and assimilate firm-level technological information. Models 4 and 6 in Table 4 test the interaction between Patents Familiarity and TRD. Consistent with our interpretation, the interaction is negative (coeff. = −5.656, p = .004 in Model 4; coeff. = −5.601, p = .005 in Model 6).

The US patent system is designed to promote the disclosure of technological information to the general public in exchange for a temporary legal monopoly on an innovation

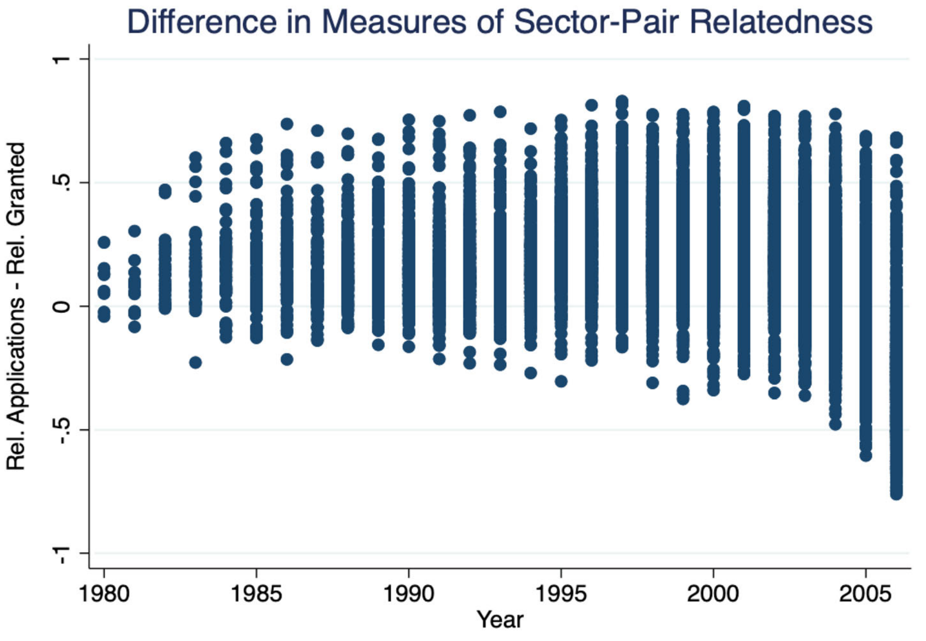

FIGURE 2 Difference between calculating sector-pair relatedness (cross-citations) using patent applications versus patent granted.

(Williams, 2017). In line with this goal, the USPTO publicly releases its comprehensive repository of codified information, which investors can use to reduce information asymmetry when evaluating technological synergies. USPTO patent data not only provide useful insights into a target firm's technology and its applications but also shed light on competitors' technologies. Chondrakis et al. (2021, p. 1031) highlight how patent information is widely used to track changes in the technological landscape and monitor firm innovation. Technological platforms such as Clarivate's Derwent Innovation tool and LexisNexis' IP analytics have greatly facilitated investors' access to the vast amount of information contained in patents (Chondrakis et al., 2021; Rivette & Kline, 2000). The available information includes the scope and uses of patented technologies, specifying potential applications in distinct markets (Barber & Diestre, 2022).

As with the previous argument, we expect that the overall technological information environment surrounding a firm and its competitors may also influence the extent of mispricing due to TRD. Characteristics of the patent system, such as the lag between patent application and publication or whether rejected patents are published at all, may affect investors' ability to track technological changes and understand a firm's position in the technological ecosystem.

To test this idea, we follow Chondrakis et al. (2021) and use the American Inventors Protection Act (AIPA) of 1999 as an information shock. The AIPA required US patent applications filed after November 29, 2000, to be published 18 months after their priority date,[12] with the earliest batch of information released on May 29, 2002. This reform accelerated the disclosure of information that would eventually be published in granted patent documents. It also exposed

[12]The priority date is the first date of filing of a patent application. It is essential for determining whether any subsequent application for the same invention can still be assessed as novel.

information that was previously confidential, such as details about rejected or withdrawn patent applications and correspondence with patent examiners.

To understand the significance of the AIPA for improving investors' understanding of TRD, we plot in Figure 2 the difference between estimates of sector-pair relatedness (i.e., the number of sector pair cross-citations over a 5-year rolling window) using patent applications versus granted patents.[13] As shown, at any given point in time, using the most recent information may yield a different picture of the technological relationship between sectors. The variance in the difference between the two measures also appears to grow over time, possibly due to increased patenting activity and a faster pace of technological development. Prior to the AIPA, patent application information was hidden from investors, likely increasing uncertainty. Moreover, as patent claims are often reduced during the transition from application to granted patent (e.g., Marco et al., 2019), granted patents may be less informative than the original applications, especially when the claims reflect the broader applicability of a technology.

However, not all SIC4 sectors were equally affected by the new regulation. In some sectors, the patent application process is notably faster than in others, meaning that the impact of the AIPA in these sectors should be smaller, allowing for sufficient heterogeneity to conduct the analysis. Our key independent variable for this test, Time-to-Grant, is calculated as the average time lag in months between patent application and publication for the period 1996–2000. We aggregate the Time-to-Grant at the firm level by computing an average based on segment sales. Note that all firm-level variation in Time-to-Grant comes from segment sales averaging, since the patent granting delay is estimated at the SIC4 level. Empirically, we test the effect of the AIPA on TRD mispricing by estimating the three-way interaction "TRD × Post-AIPA × Time-to-Grant," with the final regression model taking the following form:

$$\begin{aligned}\alpha_{it} = {} & a_t + b_1 TRD_{i,t} + \beta W_{i,t} + b_2 TRD_{i,t} * TimetoGrant_i + b_3 TRD_{i,t} * PostAIPA_t \\ & + b_4 TimetoGrant_i * PostAIPA_t + b_5 TRD_{i,t} * PostAIPA_t * TimetoGrant_i + u_i + y_t + \varepsilon_{i,t},\end{aligned} \tag{4}$$

The estimation of Equation (4) allows us to test whether the impact of TRD on stock market mispricing is reduced as a result of the AIPA. We can see this by deriving the marginal impact of TRD on stock market mispricing in (4) as:

$$\frac{\partial \alpha_{it}}{\partial TRD_{i,t}} = b_1 + b_2 TimetoGrant_i + b_3 PostAIPA_t + b_5 PostAIPA_t * TimetoGrant_i. \tag{5}$$

(5) implies that:

$$\text{If PostAIPA} = 1 \text{ then } \frac{\partial \alpha_{it}}{\partial TRD_{i,t}} = b_1 + b_2 TimetoGrant_i + b_3 + b_5 TimetoGrant_i;$$

while if PostAIPA = 0 then $\frac{\alpha_{it}}{\partial TRD_{i,t}} = b_1 + b_2 TimetoGrant_i$.

[13]The difference is calculated as: (cross-citation patent applications − cross-citation patent granted)/(cross-citation patent applications + cross-citation patent granted), such that the resulting difference value is bounded between 1 and −1. Positive values mean that the relatedness using the most recent information (i.e., patent applications) is higher than relatedness using patent granted, the opposite for negative values.

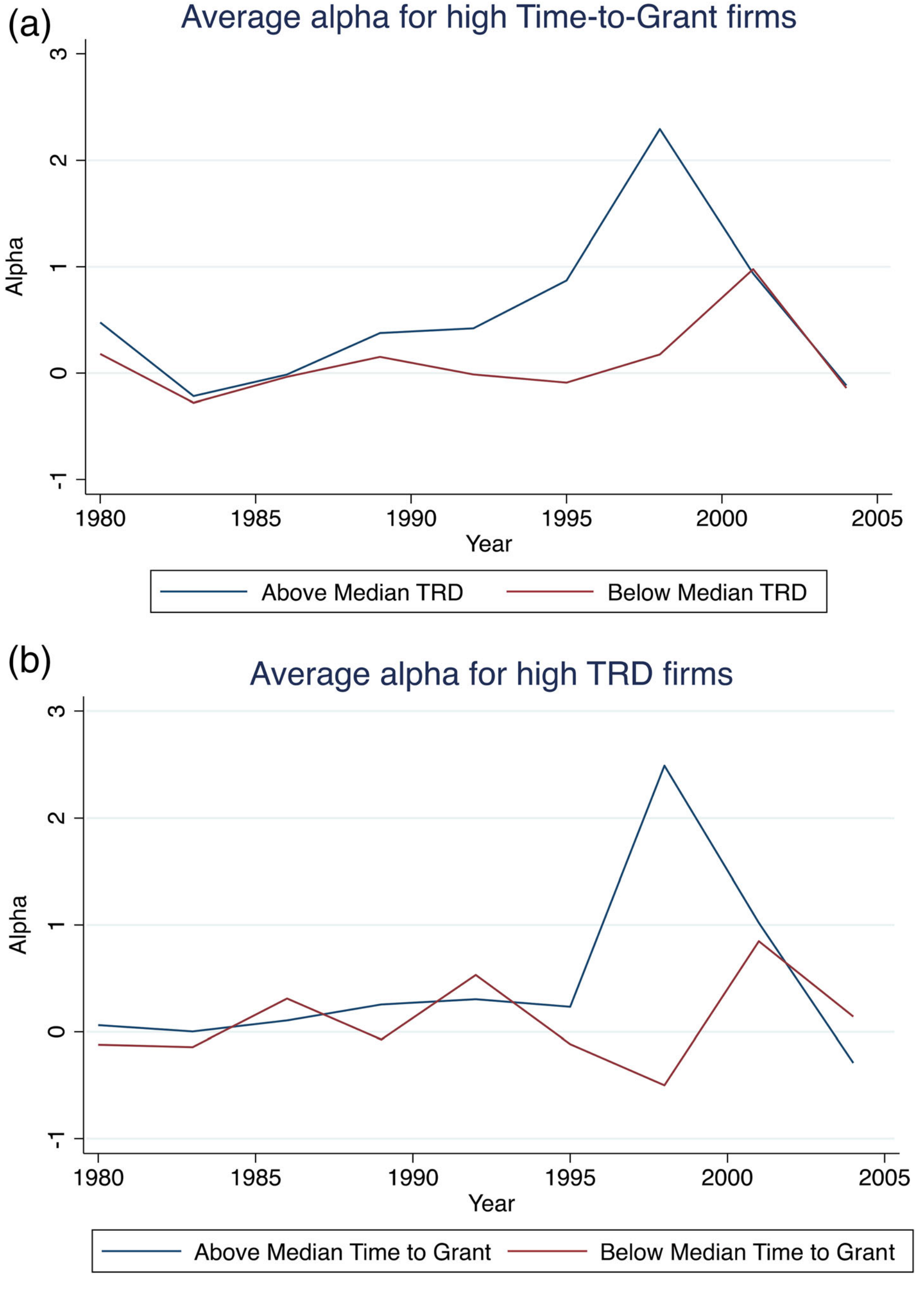

FIGURE 3 (a, b) Trends in alpha across groups.

Hence, the effect of AIPA on the relationship between TRD and stock market mispricing is equal to $b_3 + b_5 TimetoGrant_i$. Our hypothesis is that $b_5 < 0$ since the marginal impact of TRD on Alpha should decrease more for those sectors in which the lag from patent application to grant is longer. For these sectors in fact, the AIPA released a larger amount of information which previously would have been kept secret for a longer time.

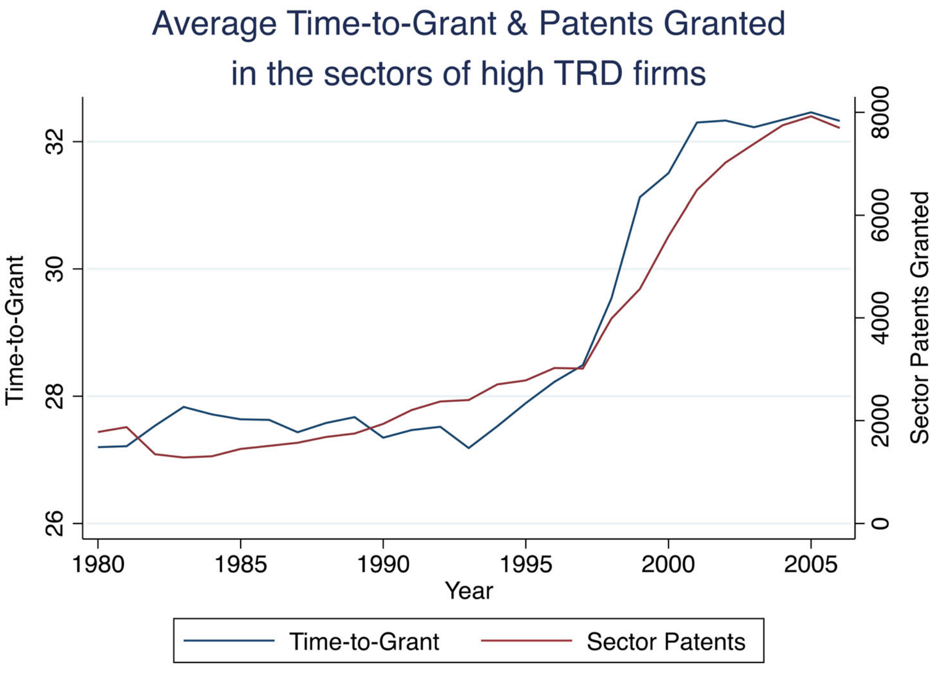

FIGURE 4 Average time lag in months between patent application and grant and average number of patents granted in the sectors of high TRD firms.

Given that this empirical setup is a difference-in-difference design with heterogeneous treatment, we begin by visually inspecting the trend in alpha across groups to assess the validity of the parallel trend assumption underlying the methodology. Specifically, in Figure 3a, we select firms operating in sectors in the highest quartile of Time-to-Grant and partition them into two groups based on TRD. In Figure 3b, we follow a similar approach but select the highest quartile of TRD and split the firms at the median for Time-to-Grant. As shown, regardless of the partitioning method, the two groups exhibit similar behavior in the pre-treatment years up until 1995. In 1998, the high TRD and high Time-to-Grant group shows a spike in alpha, which then converges to the level of the low TRD and low Time-to-Grant group by 2001, the first post-treatment year.

We believe the explanation for this pre-treatment spike can be found in Figure 4, where we plot the trend in Time-to-Grant and patent grants for high TRD firms. The figure shows that starting in 1995, there was a surge in patent applications by this group of firms. These applications likely caused a backlog at the USPTO, leading to longer delays between patent application and granting. This increase in patenting and the corresponding delays may have created greater opacity, which could explain the rise in alpha during the final pre-treatment period. Despite this plausible explanation, the spike in alpha violates the parallel trend assumption crucial for standard difference-in-difference methodology. To address concerns arising from this potential violation and the heterogeneous nature of treatment intensity in our setting, we perform a robustness check. We employ a matching procedure combined with the Wald-TC estimator proposed by de Chaisemartin and D'Haultfœuille (2020), implemented via the *did_multiplegt* routine in Stata. This approach is specifically designed to be more robust to violations of the parallel trends assumption under certain conditions and accommodates variations in treatment intensity across firms. This analysis (details available upon request) corroborates the findings presented below.

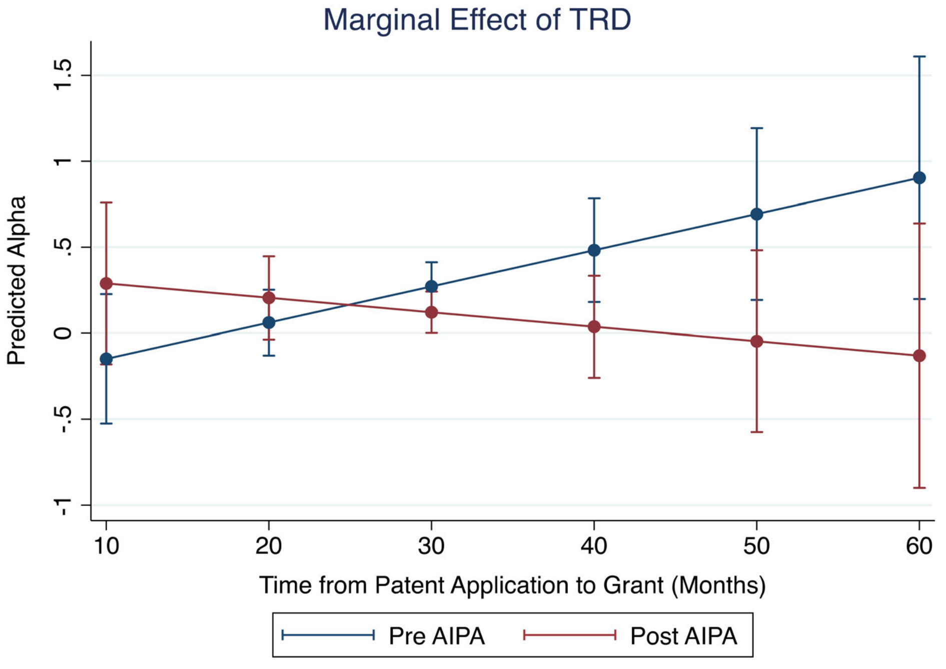

FIGURE 5 Marginal effect of TRD, pre- and post-AIPA depending on patent Time-to-Grant (95% confidence level).

In Regressions 5 and 6, we examine the effect of the three-way interaction between the post-AIPA dummy (set to 1 starting in 2002), the Time-to-Grant variable, and TRD. As expected, the interaction is negatively associated with alpha (coeff. = −0.029, $p = .005$ in Model 5; coeff. = −0.027, $p = .010$ in Model 6). Figure 5 plots the marginal effect of TRD (Equation 5) before and after the AIPA, for values of Time-to-Grant within the first and last percentiles of our sample. As shown, pre-AIPA, the positive effect of TRD on alpha increases with the sector time lag between patent application and grant. This positive slope before AIPA suggests that the time it took for information contained in patent applications to become public (when patents were granted) amplified the impact of TRD on stock market mispricing. In contrast, post-AIPA, this relationship seems to disappear, as indicated by the large confidence intervals of the point estimates, suggesting little difference between the effect of TRD across granting lags. While the robustness check using a method better suited for these conditions provides additional support, given the aforementioned pre-treatment dynamics, we maintain caution and refrain from making causal interpretations based on this evidence.[14]

[14]In unreported analyses we perform a sample split to test whether the effect of the AIPA is driven by firms with the highest level of discrepancy between TRD estimated using patent applications and TRD estimated using patents granted. If the sudden release of technical information caused by the AIPA allowed to update estimates of technological synergies, then it should be the case that the impact of the event is more meaningful for those firms with higher discrepancy between TRD computed using patent applications versus using patents granted. For these firms investors should update their expectations about future performance partly eliminating abnormal returns. Consistent with this idea, we find that the effect of the negative three-way interaction is only different form zero in the subsample of firms exhibiting an above the median level of discrepancy.

TABLE 6 Sector adjusted alphas and robustness tests.

	Alpha on firm—sector return						Alpha—sector alpha	Alpha on firm—comparable return	Alpha—comparable alpha
Alpha adjustment	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
TRD	0.197	0.165	0.244	0.377	−0.068	0.192	0.122	0.177	0.158
	(.001)	(.014)	(.001)	(.000)	(.841)	(.590)	(.037)	(.007)	(.018)
TRD × Investors' attention		−0.279				−0.317			
		(.113)				(.071)			
TRD × Analysts' coverage			−0.017			−0.015			
			(.090)			(.141)			
TRD × Pat. Familiarity				−6.314		−5.767			
				(.001)		(.005)			
TRD × Time-to-Grant × Post AIPA					−0.022	−0.020			
					(.043)	(.074)			
Investors' attention		2.759				2.772			
		(.001)				(.002)			
Analysts' coverage			−0.011			0.021			
			(.802)			(.623)			
Patents Familiarity	−1.167	−0.749	−1.132	4.825	−1.006	4.755	−2.200	−2.020	−2.678
	(.748)	(.836)	(.755)	(.220)	(.780)	(.228)	(.538)	(.589)	(.482)
TRD × Time-to-Grant					0.010	0.007			
					(.418)	(.562)			
TRD × Post-AIPA					0.652	0.564			
					(.045)	(.085)			
Time-to-Grant × Post-AIPA					−0.007	−0.011			
					(.809)	(.705)			

TABLE 6 (Continued)

	Alpha on firm—sector return						Alpha—sector alpha	Alpha on firm—comparable return	Alpha—comparable alpha
Alpha adjustment	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Post AIPA					1.353	1.599			
					(.157)	(.099)			
Time-to-Grant					0.013	0.012			
					(.589)	(.632)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4588	4588	4588	4588	4588	4588	4588	4484	4484
Adj. *R*-sq	0.045	0.048	0.046	0.048	0.046	0.054	0.032	0.043	0.039

Note: Two-tail *p*-value in parenthesis below the coefficient. The dependent variable in Models 1–6 is sector adjusted alpha, estimated on the difference between firms' monthly returns and normal sector returns. In Model 7 we test a variation of the procedure where we subtract from firm's alpha its corresponding normal sector alpha. In Model 8 we use matching adjusted alpha as the dependent variable. This variable is calculated by subtracting from the firm's returns the returns of matched focused competitor. Finally in Model 9 we again test a variation where we subtract from firm's alpha the alpha of the matched focused firms. Please refer to the in-text explanation for further details.

Overall, the evidence is consistent with the idea that both stock market participants' attention and the amount and type of information released by firms and the patent system can influence the mispricing associated with TRD strategies.

4.3 | Sector adjusted result and robustness tests

A potential concern regarding our main result is the possibility that we might be confounding the effect of TRD with the more general effect of technological intensity. Under this alternative view, investors might generally struggle to price technology, and this could explain the observed alpha, with TRD and technological synergies simply being correlated factors. While our baseline analyses already account for technological intensity through fixed effects and control variables, in Table 6 we use different methodologies to adjust the dependent variable and fully eliminate variance arising from sector- or firm-specific technological intensity.

In Regressions 1–6, we replicate the results from Table 4 on firm alphas estimated from the difference between firm and sector returns. We begin by calculating the 2-digit SIC sector monthly returns, constructing value-weighted portfolios of single-segment firms operating in the same SIC2 sector. For each firm, we then calculate a "normal" sector return by averaging the returns of the portfolios of its operating sectors, weighted by segment assets:

$$Normal\ Sector\ Ret_{i,t,m} = \sum_{s=1}^{N} w_{s,t} \times SIC2\ Portfolio\ Ret_{s,t,m}, \tag{6}$$

where N is the number of SIC2 segments of firm i in year t; $w_{s,t}$ is the percentage of assets that segment s represents over the total of firm i in year t; and $SIC2\ Portfolio\ Ret_{s,t,m}$ is the monthly return of the SIC2 portfolio corresponding to segment s of firm i in year t. Firm i sector adjusted monthly return are then equal to:

$$Sector\ Adjusted\ Ret_{i,t,m} = Ret_{i,t,m} - Normal\ Sector\ Ret_{i,t,m}. \tag{7}$$

This subtraction removes any over- or under-performance due to sector effects, including sector technological intensity, leaving only the component attributed to technological synergies. We use the Sector Adjusted Return to estimate 3-year, firm-level, four-factor alphas using the same procedure as in Table 4. The results from Models 1 to 6 in Table 6 are consistent with those reported in Table 4.

In Regression 7, we test a variation of this procedure by separately estimating 3-year SIC2 portfolio alphas. We then adjust firms' alphas by subtracting the weighted average, based on segment assets, of the operating SIC2 sector alphas.

In Regression 8, we perform an adjustment that places more weight on firm-specific technological intensity, while still accounting for sector-level variation. Specifically, we compare the returns of diversified firms to those of matched "synthetic firms" created using the returns of specialized competitors with comparable levels of technological intensity. We begin by calculating the diversified firms' matching-adjusted monthly returns, subtracting from their monthly returns the estimated normal returns, given their participation in industries, size, and technological intensity. To estimate these normal returns, we match each operating segment with five focused competitors based on the shortest Mahalanobis distance, calculated using the log of segment sales, R&D intensity, and the log of the segment patent portfolio.[15] We impose restrictions on the 2-digit SIC sector and year to ensure that each matched focused firm observation corresponds to the same period and industry as the diversified firm's segment. The monthly return of the synthetic firm is calculated by first computing the normal segment monthly returns. For this, we take the simple average of the monthly returns of the five single-segment firms matched to each segment. We then average these normal segment returns, weighted by segment assets, to estimate synthetic firm returns. Formally:

$$SyntheticFirmRet_{i,t,m} = \sum_{s=1}^{N} w_{s,t} \times Normal\ Segment\ Ret_{s,t,m}, \tag{8}$$

where N is the number of segments of firm i in year t; $w_{s,t}$ is the percentage of assets that segment s represents over the total of firm i in year t; and $Normal\ Segment\ Ret_{s,t,m}$ is the monthly average return of the five focused firms matched to each segment s of firm i in year t. Firm i matching adjusted monthly returns are then equal to:

$$Matching\ Adjusted\ Ret_{i,t,m} = Ret_{i,t,m} - Syntetic\ Firm\ Ret_{i,t,m}. \tag{9}$$

Given the similarity between diversified firms and their synthetic counterparts, this subtraction removes any over- or underperformance due to firm- and sector-specific technological intensity, leaving only the component due to technological synergies. We use the Matching Adjusted Returns to estimate 3-year matching-adjusted alphas, which we then test for their association with TRD in Model 8.

In Model 9, we test another variation of the procedure from Model 8 by separately estimating 3-year synthetic firm alphas. We then adjust firms' alphas by subtracting the corresponding synthetic firm alpha.

The test of the main effect of TRD in Models 1 (coeff. = 0.197, p = .001), 7 (coeff. = 0.122, p = .037), 8 (coeff. = 0.177, p = .007), and 9 (coeff. = 0.158, p = .018) yields results consistent with those reported in the main analysis of Table 4, reinforcing the conclusion that our results are not due to technology per se, and that the synergies generated by TRD firms are underpriced.

5 | DISCUSSION AND CONCLUSIONS

Driven by the critical importance of product-market diversification for business success, investigations into the effects of related and unrelated product-market diversification are central to corporate strategy research (e.g., Gary, 2005; Markides & Williamson, 1994; Palich et al., 2000). A significant body of literature has explored the consequences of various relatedness strategies on accounting performance, stock market capitalization, and several operational outcomes that

[15]We use the average R&D intensity of the firm as a proxy for the R&D intensity of the segment. The patent portfolio of each diversified firms' segment is estimated by dividing the total patent portfolio of the firm based on the share of total firm sales that each segment represents. This essentially means that if firm A has 10 patents and operates in two segments, x with sales of 30 and y with sales of 70, for the purpose of matching we consider segment x's patents to be 3 and segment y's patents to be 7.

mediate the positive effects. In this article, we build on the literature linking technological relatedness to performance (Chari et al., 2008; Miller, 2006; Stern & Henderson, 2004; Tanriverdi & L, 2008) to address a related but distinct question: When TRD is linked to better performance, do stock market prices accurately reflect this expectation? Our results suggest that they do not, and this can be attributed to the difficulties investors face when evaluating complex strategies, compounded by limited attention (Hirshleifer et al., 2018; Lee et al., 2019; Litov et al., 2012; Oehmichen et al., 2021).

Using both portfolio analysis and standard panel OLS regressions, we show that TRD firms generate outsized positive returns relative to their level of risk. The size of these returns is large enough to be meaningful, ranging from 3.17% to 5.25% per year, depending on the estimation. Positive abnormal returns indicate stock market mispricing, unless TRD increases the total level of risk for a firm's stock. While some management theories link TRD to undesirable outcomes (e.g., Shaver, 2006), such as increased coordination costs or the spread of negative technological shocks, our explicit tests of the TRD proxy on the probability of bankruptcy and stock idiosyncratic volatility—outlined in the article's Supporting Information—suggest that, overall, TRD firms are less risky than other diversifiers.

This study contributes to the TRD literature by providing evidence that TRD strategies are systematically undervalued in the stock market. We attribute this mispricing to the complexity investors face when evaluating TRD's technological synergies. Supporting this view, our empirical analysis shows the TRD association with abnormal returns holds even after controlling for technological novelty in a subsample of firms with unique diversification strategies, thereby isolating TRD's inherent complexity as a distinct driver.

We can gauge the magnitude of this discount by comparing the value of two income series: one yielding 11.88% per year (equal to the S&P 500's historical average annual return) and another yielding 15.05% per year (the S&P 500 value plus a conservative estimate of the abnormal TRD return) in perpetuity. Assuming the cost of capital for TRD firms is the same as for the S&P 500 (i.e., 11.88%), if the first perpetuity is worth 100, the second should be worth 127 (i.e., 15.05/0.1188). An investor who fails to distinguish between the two groups would incorrectly attribute a 21% discount to the stock of TRD firms relative to their actual value.

From a governance perspective, the failure to recognize TRD's value creation is problematic, as it might lead to suboptimal strategic choices. In a classic agency theory scenario, where management career and compensation depend on the company's stock performance, superior value-creating strategies might be discarded in favor of actions that are more easily communicated to outside investors.

Our analysis also identifies situations in which the problems stemming from limited investor attention are mitigated. By using OLS regressions on firm-level alpha estimates (see Table 4) to test moderating factors, we show that the degree of attention stock market participants devote to TRD firms, the novelty/familiarity of firm-level technological information, and the size and timing of technological information releases by the patent system all influence the relationship between TRD and abnormal returns. Firms with a lower presence of transient institutional investors—those focused on short-term gains—are better able to have their fundamental value reflected in stock prices. Firms with patent information using more familiar terminology, which is easier to interpret, also tend to experience reduced discounts. Furthermore, following the enactment of the AIPA, we observe a decrease in the magnitude of abnormal returns for firms with more public information released. This highlights the importance for investors of monitoring recent technological developments contained in patent applications, which were previously only made public after patent granting.

While it is important to note that our evidence is suggestive due to the lack of robust causality tests, it indicates that firms may benefit from two key actions. First, monitoring the readability of technological information released to the public can be advantageous. Second, keeping investors updated on early-stage technology development projects may prove valuable.

Finally, our study has some limitations. First, we do not have direct observations of investors' valuation processes when it comes to technological synergies. What pieces of information do they rely on when assessing the merit of a diversification strategy (e.g., patent applications, patents granted, parts of financial statements, or management calls with analysts)? Researchers with access might develop questionnaires to understand financial analysts' thinking processes in issuing price targets and buy/sell recommendations. Obtaining such evidence would help provide better managerial guidance in reducing asymmetric information.

Second, while our study focuses on TRD, it is an open question whether other related diversification strategies experience the same asymmetric information problem. Relatedness strategies that leverage a common brand or an effective supply chain might be more easily understood by external investors because their contribution is more visible, even from outside the firm. Conversely, strategies that rely on particularly talented human capital could face the same undervaluation issue, as assessing the quality of a company's talent pool might prove difficult from the outside.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from third-party sources. Financial and market data were obtained from the CRSP and Compustat databases via Wharton Research Data Services (WRDS) and are available under license. Restrictions apply to the availability of these data. Patent data were obtained from the NBER patent database, which is publicly available. Licensed data are available from the authors with the permission of WRDS.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Morandi Stagni, R., & Santaló, J. (2025). Investors' attention and the paradox of technologically related diversification: Evidence of stock market mispricing. *Strategic Management Journal*, *46*(10), 2432–2466. https://doi.org/10.1002/smj.3726