How Does Earnings Pressure Inhibit Corporate Innovation?

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ABSTRACT

This study investigates how managing earnings as a reaction to earnings pressures from the capital market can affect a firm's innovation approach. While most studies have viewed managing earnings as "managing costs," I propose that, since earnings pressure alters the cost of waiting and preference for predictability, managers can respond to earnings pressure by "managing revenues"; thus, pursuing more rapid and reliable results. Consequently, managers adjust the allocation of the research efforts, affecting the type and quality of innovation outcome. Applying a difference-in-differences specification I found that, after the adoption of mandatory quarterly reporting, firms suffered a decline in the use of basic science and in the breadth of their technological search, followed by a drop in the innovation quality and the probability of breakthroughs

Keywords: innovation; R&D resource allocation; managing earnings; science; technological diversification

INTRODUCTION

Pressures from capital market actors can trigger managerial reactions that influence firms' strategies (e.g., Bushee, 1998; Zuckerman, 2000). In particular, earnings pressure refers to the situation in which managers are induced to focus on short-term performance to meet earnings expectations from the capital market (Healy & Wahlen, 1999; Porter, 1992). A broad range of literature has provided evidence that managers often react to earnings pressure by "managing earnings" (Rahmandad, Henderson, & Repenning, 2018), which implies changing firms' activities and investments to pursue short-term objectives (Ernstberger, Link, Stich, & Vogler, 2017; Kraft, Vashishtha, & Venkatachalam, 2018; Rahmandad et al., 2018). However, these reactions are not necessarily aligned with the long-term firm value. When these changes in activities and investments happen at the expense of uncertain and long-term opportunities, managing earnings is considered myopic (Brav, Graham, Harvey, & Michaely, 2005; Healy & Wahlen, 1999).

Innovation activities, being future-oriented, highly uncertain, and rarely measurable in terms of performance (Holmstrom, 1989), constitute undoubtedly the most crucial strategic decision that can be affected by myopic behaviors. Anecdotal evidence reports innovation as one of the main activities that managers are willing to sacrifice when experiencing earnings pressure from the capital market (Graham, Harvey, & Rajgopal, 2005). Therefore, managing earnings is commonly considered detrimental for corporate innovation and, consequently, negatively impacts a firm's future performance (Porter, 1992).

Causal evidence of the myopic consequences of earnings pressure on innovation output is inconclusive. Although some studies have found evidence of earnings pressure reducing the number of a firm's produced patents (Fu, Kraft, Tian, Zhang, & Zuo, 2020; He & Tian, 2013), others have highlighted an efficiency effect that, in some circumstances, improves the innovation output (Benner, 2010; Brav, Jiang, Partnoy, & Thomas, 2008; Clarke, Dass, & Patel, 2015; Guo, Pérez-Castrillo, & Toldrà-Simats, 2019). However, the idea that earnings pressure can improve innovation by enhancing efficiency clashes with the crucial prerequisite of trial-and-errors and failure tolerance for stimulating innovation (e.g., Manso, 2011), and with the evidence that markets undervalue innovation efficiency (Hirshleifer, Hsu, & Li, 2013).

To understand better how earnings pressure can inhibit innovation, I argue that it is necessary to disentangle managing earnings into two distinctive sets of actions: *managing costs* and *managing revenues*.

Most of the existing literature has researched the myopic consequences of managing earnings in terms of managing costs (i.e., by cutting costs, expenditures, and investments to improve current profits). For instance, several studies have tried to determine the repercussions of earnings pressure on R&D investments (e.g., Aghion, Van Reenen, & Zingales, 2013; Bushee, 1998; He & Tian, 2013). The idea is that managers often react to earnings pressure by lowering

R&D costs to increase current earnings; thus, "borrowing" earnings from the future at an unfavorable rate (Stein, 1989). However, finding effects on R&D can be misleading (Laverty, 1996). First, managers can discretionarily change accounting R&D capitalization without decreasing the overall level of investment (Canace, Jackson, & Ma, 2018; Dinh, Kang, & Schultze, 2016). Second, managers can be reluctant to lower R&D investment since this can be counter-effective if spotted by the market (Gentry & Shen, 2013). Third, managers can use R&D investments as a legitimacy signal to the market, fueling inefficient long-termism and overinvestment in innovation (Ahuja & Novelli, 2017).

Nonetheless, one can argue that managers can also respond to earnings pressure by pursuing a different set of actions directed toward achieving quicker, smoother, and more reliable revenues (i.e., by managing revenues). Although theories on and evidence of the myopic consequences of managing costs on innovation are far from conclusive, the literature has overlooked the consequences of managing revenues. In this study, I pave the way in this direction. I argue that managers under earnings pressure aim at improving current revenues by allocating resources to deliver innovation outcomes in a shorter period and in a more predictable manner. It follows that the innovation hazards of earnings pressure do not come necessarily from a lower level of inputs (i.e., from managing costs); conversely, they are a byproduct of a transformed innovation approach aimed at improving current revenues (i.e., managing revenues), which impacts corporate innovation in terms of *type* and *quality*. Therefore, I postulate and test the idea that earnings pressure shifts managers' incentives to allocate research efforts (i) away from basic science and (ii) toward a more concentrated and specialized set of technological areas. The reduced reliance on scientific knowledge and the narrower knowledge base impair a firm's ability to find and exploit high-quality ideas (Cohen & Levinthal, 1990; Fleming, 2002). This leads to a (iii) lower average quality of the innovation output and lessens the probability to achieve breakthrough discoveries.

Empirically, disentangling the consequences of earnings pressure on a firm's innovation outcomes conveys strong causality concerns. First, this study required an empirical setting in which I could measure the extent of the earnings pressure perceived by managers. In this regard, the accounting literature has identified the frequency of reporting as a strong antecedent of earnings pressure (Ernstberger et al., 2017; Gigler, Kanodia, Sapra, & Venugopalan, 2014; Kraft et al., 2018). Second, I needed to isolate an exogenous change in the earnings pressure for a group of firms while comparing it with a control group. Inspired by accounting literature, I applied a novel "quasi-experimental" empirical setting by exploiting the European Transparency Directive of 2004 (TD; Ernstberger et al., 2017), which required member states to adopt mandatory quarterly reporting, introducing an exogenous shock in the earnings pressure. Specifically, I applied a difference-in-differences (DID) approach to compare a group of European firms in stock markets that had to change their regulatory status from semiannual to quarterly reporting, with a control group of firms in European stock markets in which mandatory quarterly reporting was already in place. The results confirm that, relative to the control group, firms in the treatment group suffered a significant decline in the level of scientific intensity and in the breadth of their technological diversification after the introduction of mandatory quarterly reporting. The data also indicate that the number of non-granted applications significantly decreased in the following years, confirming that the firms concentrated research efforts into fewer, better-known areas. In the subsequent years, the examined firms reported a lower quality of their granted patent applications, both in terms of average value and as a percentage of breakthroughs.

This study provides a number of contributions. First, it reconciles some of the existing mixed evidence and theories regarding the myopic vs efficiency effects of earnings pressure on innovation by introducing a different standpoint of managing earnings. To obtain results in the short term, managers do not necessarily renounce innovation but change how they innovate. In this way, this study also contributes to the literature examining how the capital market pressures affect innovation not only in terms of input level (i.e., R&D investments), but also innovation *type* (Fitzgerald, Balsmeier, Fleming, & Manso, 2020). Second, this study contributes to the literature on the consequences of short-termism (Reilly, Souder, & Ranucci, 2016) by shedding new light on the decisions concerning resource allocation among research projects (Budish et al., 2015). Third, this study adds to the literature studying performance feedback (Gavetti, Greve, Levinthal, & Ocasio, 2012) by providing new empirical evidence regarding how the increased frequency of performance evaluation can feed back into the organization of innovation activities and, ultimately, their outcome.

BACKGROUND

Managing Earnings and Corporate Innovation

Accounting and financial literature has found that managers react to earnings pressure by "managing earnings" through real business decisions and the reallocation of resources (Bartov, 1993; Brav et al., 2005; Ernstberger et al., 2017; Kraft et al., 2018). Managing earnings refers to the set of manager actions and decisions expressing an extreme interest in current earnings with respect to the future firm's value. Especially when it is difficult for market actors to observe the underlying managerial ability, managers might tend to "borrow" earnings from the future at an unfavorable rate to increase the current ones (Stein, 1989). Therefore, managing earnings as a response to earnings pressure can generate managerial myopia, discouraging a firm's investment in long-term, uncertain activities and compromising future competitiveness and performance (Laverty, 1996; Porter, 1992).

The main reason managing earnings as a response to earnings pressure is considered problematic for a firm's future value is the consequences it can have on innovation activities. Innovation projects require time to explore and experiment with different solutions and development paths; failures are common, and there is often a lack of established routines and practices which makes performance measures rarely available (Holmstrom, 1989).[1] Therefore, innovation activities can be highly exposed to the consequences of earnings pressure.

However, despite anecdotal evidence (Graham et al., 2005), robust causal confirmations of the myopic consequences of earnings pressure on innovation output are inconclusive. For instance, diverse studies on earnings pressures induced by corporate governance mechanisms have provided contrasting results (e.g., see Aghion et al., 2013; Atanassov, 2013; Bertrand & Mullainathan, 2003; Karpoff & Wittry, 2018; and the replication study of Keum, 2020). Similarly, a reduction of the number of patents has been found due to earnings pressure created by analysts' coverage (He & Tian, 2013). Furthermore, accounting literature studying the regulatory changes in reporting frequency in the United States (US) in 1955 and 1970 has found that earnings pressure caused a decline in the number of patents and citations, given the level of R&D input (Fu et al., 2020). Conversely, others have found that earnings pressure from capital market actors plays an active role in disciplining firms, favoring innovation in the most productive ones (Clarke

[1] Innovation activities require important upfront costs (Hall, Jaffe, & Trajtenberg, 2005), but their attributes are hardly understood by third parties (Rajan & Zingales, 2001), and little interim information throughout the long gestation period of innovation process is available (Goodacre & Tonks, 1995). Moreover, innovation activities are highly exposed to evaluation errors (Carpenter & Petersen, 2002).

et al., 2015), influencing specific types of innovation strategies (Benner, 2010), and enforcing a more efficient use of innovation resources (Guo et al., 2019). Still, why earnings pressure should improve innovation by enhancing efficiency is not clear. Efficiency logic contrasts with trial-and-errors and failures tolerance, which are crucial antecedents of innovation (Manso, 2011). For instance, stringent reporting in healthcare have been revealed to induce doctors to be risk adverse, declining treating high-risk clients (Dranove, Kessler, McClellan, & Satterthwaite, 2003). Finally, innovation efficiency is difficult to evaluate, and firms more efficiently applying R&D resources tend to be undervalued by the market (Hirshleifer et al., 2013). What emerges from the current state of the literature is that neither myopic nor efficiency arguments seem to provide consistent answers, either empirically or theoretically.

Managing Earnings as *Managing Costs*

Most of the literature has researched the consequences of managing earnings on corporate innovation from the standpoint of managing costs. Managers can respond to earnings pressure by cutting costs, reducing expenditure, or lowering investment levels to improve current profits. Regarding corporate innovation, managing costs means reducing R&D inputs. Many studies have found that earnings pressure may induce firms to cut R&D expenses, for example, after a leveraged buyout (Long & Ravenscraft, 1993), or after missing analysts' forecasts the previous year (Gentry & Shen, 2013), or because of transient ownership (Bushee, 1998). However, the innovation consequences of earnings pressure as managing costs can be misleading (Laverty 1996). First, managers can exercise discretionary R&D accounting capitalization as opportunistic earnings management, moving R&D costs from expenses to capitalization (Canace et al., 2018; Dinh et al., 2016). Second, even if managers are reluctant to invest in R&D activities, investors tend to display a favorable attitude toward R&D investments (Chauvin & Hirschey, 1993). This can lead managers to use R&D as a legitimation signal of "good management" (Ahuja & Novelli,

2017) and be less willing to cut those innovation costs that can negatively affect a firm's evaluation (Gentry and Shen 2013). Third, a firm's competitiveness not only depends on the input level of R&D investments, but also on how the firm can capitalize on such investment. Earnings pressure could, therefore, nurture inefficient overinvestment in R&D (Ahuja & Novelli, 2017). Consequently, some studies have found that even if earnings pressure causes firms to reduce investment in R&D, they experience higher return on assets in the future (e.g., Gunny, 2010).

Managing Earnings as *Managing Revenues*

Managers can also respond to earnings pressure by pursuing a different set of actions in addition to cost reduction, which is managing revenues. Managers can improve current earnings by achieving quicker, smoother, and more reliable revenues. However, the literature has overlooked the consequences of earnings pressure regarding managing revenues. Psychological literature has suggested that the decision-making cognitive process is subject to a multidimensional evaluation, assessing the amount, the delay, and the probability of the reward (Green & Myerson, 2004). Consequently, managers under earnings pressure can respond by favoring activities that promise outcomes with a shorter delay and that are more reliable. The delay is usually indicated in terms of *cost of waiting*, whereas the probability of the outcomes relates to the *predictability*. In this section, I explore these two mechanisms that explain how earnings pressure can induce managers to manage earnings by pursuing quicker and smoother results.

Cost of Waiting. Managers under earnings pressure have a higher cost of waiting. This cost comes from the long-term benefits of an economic action taking time to be achieved, creating a mismatch between the timespan of the investment and the time available to managers to demonstrate success (Bower, 1972). Classic and behavioral economics considers the cost of waiting in terms of the impatience of an actor waiting for a result to be achieved (Loewenstein &

Thaler, 1989, Soman et al., 2005). This impatience refers to the phenomenon of an immediate reward being more attractive than the same reward later, due to time discounting (Samuelson, 1937). For instance, investors can become impatient and respond quickly to changes in the current performance (Froot, Scharfstein, & Stein, 1992). As such, the most common popular intuition considers earnings pressure to be caused by impatient traders in the capital market who demand quick returns to managerial actions, increasing the managerial cost of waiting. However, without considering the predictability of the results, this is view is incomplete (Gigler et al., 2014; Stein, 1989).

Predictability. Managers under earnings pressure display higher preferences for more predictable results. This is because of information asymmetry between firms and investors, which creates difficulties capturing, in the current stock prices, the long-term benefits of firms' economic actions, even if adequately discounted for waiting. Current prices should depend on the buyers' evaluation, which is based on their expectations of future prices; even if the buyer is impatient, the evaluation relates to the expected prices of reselling (i.e., how much the succeeding buyer will pay for the firm's stock, and so on). Thus, despite investor impatience, current prices should already capture the longer, future-expected value if full information in the market exists. However, earnings pressure arises if there is (at least) some discrepancy between the market and managers' information (Stein 1989).[2] For example, Polk and Sapienza (2008) demonstrated that

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[2] Stein (1989) explained this using a similar mechanism to the prisoner dilemma. Since the future payoff of an economic activity cannot be directly observed by an outsider, as the market cannot perfectly know the future consequences of a firm's action, managers are incentivized to mislead the market regarding the value of the firm, borrowing for the future to increase current earnings. In equilibrium, the market anticipates this and adjusts the

short-term price pressure (proxied by a high share turnover) leads to suboptimal investment for firms with investments that could be hardly observed. Furthermore, asymmetric information regarding the outcomes of managerial activities creates uncertainty, which increases with the time lag for expected results (Trope & Liberman, 2003). Every time earnings information is released, investors make premature evaluations of managerial actions whose value is probabilistically revealed only over the long term. Uncertainty makes each premature evaluation of a future outcome exposed to measurement errors that can distort market pricing (Kanodia & Mukherji, 1996; Kanodia, Sapra, & Venugopalan, 2004). Even if these premature evaluations are tempered in the moment of realization of the final outcomes, the loss caused by early, distorted, uncertain evaluations cannot be overcome when shareholders are sufficiently impatient (Gigler et al., 2014).

Taken together, cost of waiting and predictability are the two co-occurring mechanisms through which earnings pressure is translated into managerial behaviors. If investors lack the information to understand the future outcomes and the patience to wait for them, managers will suffer a higher risk of stock price devaluation. Consequently, managers are induced to improve current earnings, not necessarily by cutting costs, but by managing revenues and pursuing activities that provide results in a shorter amount of time and in a more predictable manner.

HYPOTHESES

Since earnings pressure increases the managerial cost of waiting for results, it induces managers to speed up the delivery of innovation outcomes, pushing toward technologies that can

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current evaluation, conjecturing that there is an earnings inflation. In other words, price pressure can cause the manager to behave myopically even though the market is fully efficient.

reach the final market quicker and translate into rapid earnings. In other words, earnings pressure might urge managers to push for innovation speed, which is achieved by shortening the time between the initial development and introducing a new product into the marketplace (Murmann, 1994). Similarly, since the earnings pressure increases the preference for more predictable results, it induces managers to manage revenues by lowering the expected variance around innovation results to make innovation efforts easier to be evaluated externally.

Scientific Intensity of Research Activities

The first crucial consequence relates to the decision of the level of maturity of research activities to allocate R&D resources. I argue that managers' increased cost of waiting and preference for predictability induces managers to lower the amount of research resources devote to basic science.

Cost of Waiting. The increased cost of waiting induces managers to prefer more mature technologies that are ready to be marketed. However, basic scientific discoveries are usually associated with less mature innovation (Gambardella, 1992; Rosenberg, 1989; Simeth & Cincera, 2016) and are associated with higher expected times to deliver results. Therefore, managers under earnings pressure might prefer to relocate their R&D resources to research projects with lower scientific intensity to reduce the waiting time and achieve quicker revenues.

Predictability. The increased inclination for predictability induces managers to prefer planned and reliable research projects. However, a very large part of basic research is unintentional, in which scientific discoveries emerge mostly as unplanned byproducts of attempts to solve different problems (Rosenberg, 1989). Seminal works, such as Arrow (1972) and Nelson (1959), have argued that the high degree of uninsurable risk of scientific knowledge makes firms reluctant to invest in basic science. The high variability of the results creates uncertainty and very low predictability of innovation outcomes that rely heavily on basic science. Consequently, managers under earnings pressure might allocate R&D resources away from basic science, favoring research projects in which the outcome is more predictable and that can reach the market quicker and generate economic profits. Thus, I formulated the following hypothesis.

Hypothesis 1 (H1). *An increase in earnings pressure induces a lower level of scientific intensity in corporate innovation.*

Concentration of Research Activities

The second consequence relates to the decision of the number of various technological areas to allocate R&D resources, a phenomenon known as technological diversification (Nelson & Winter, 1977; Patel & Pavitt, 1997). As research areas become more diversified, innovation investments generate inefficiencies that can delay the expected returns and decrease the associated predictability. The increased cost of waiting and preference for predictability have the following consequences.

Cost of Waiting. While the increased cost of waiting induces managers to foster innovation speed, literature has identified the diversification of project streams as negatively affecting innovation speed (Kessler & Chakrabarti, 1996; King & Penlesky, 1992; Murmann, 1994). This happens because pooling resources in fewer research areas (i) reduces friction and (ii) improves learning. First, firms with diversified research projects are likely to suffer greater friction in terms of knowledge integration and coordination (Granstrand, 1998). As knowledge transfer is easier within a firm's boundaries (Miller, Fern, & Cardinal, 2007; Teece, 1986), similar mechanisms also apply to the different R&D labs within the same company. Transaction costs may arise due to uncertainties that are intrinsic in the development of products requiring interrelated technologies controlled by different negotiating parties (Teece, 1988).[3] Moreover, project overload saturates individual attention, which is essential to the completion of new product development (Bierly & Chakrabarti, 1996; Kessler & Chakrabarti, 1996). A crowded project stream creates information overload, meaning top-level managers face increased struggles in monitoring individual activities at lower organizational levels (Hoskisson, Hitt, & Hill, 1991), resulting in some projects that become stuck, awaiting reviews and funding decisions (Smith & Reinertsen, 1992). Second, concentrating research efforts can help achieve specialization benefits, improving the learning process in fewer but more well-known core technologies (Breschi, Lissoni, & Malerba, 2003), pushing the learning curve, and facilitating employees developing the skills, knowledge, familiarity, and abilities for rapid innovation development. For instance, the size of the capacity and throughput of research resources have been found to influence knowledge development through economies of speed in the pharmaceutical industry (Nightingale, 2000). Learning is also facilitated because individuals working within the same technological research project can easily transfer knowledge among themselves, sharing a similar knowledge base, organizational codes, and language (Grant, 1996)

Predictability. While the increased preference for predictability induces managers to concentrate on fewer but more well-known areas, diversification can increase the difficulties

[3] For instance, inventors working on the development of different components may disagree about the best design of the combined product, blocking or slowing subsequent developments (Richardson, 1972). Additionally, each team has to negotiate the shared costs and benefits of technology transfer. Nonetheless, if there is disagreement regarding the different contributions to a patent, teams can create friction by holding each other up. Hence, concentrating interrelated efforts under the same coordinating authority (i.e., within the same research team) facilitates coordination through reducing the incentives to engage in eventual hold-ups (Williamson, 1975, 1991).

associated with evaluating an innovation strategy by observers external to the firms. For instance, Zuckerman (1999) found that the industry categories and unrelated diversification strategies trigger a decrease in stock price since the firm's stock is more difficult for analysts to cover. Similarly, Moreton and Zenger (2005) revealed that stock price discounts are also triggered by complex strategies that require analysts to process greater informational loads. In line with these results, Benner (2010) found evidence that analysts, in the case of technological change, are more positive toward those incumbent strategies that preserve the existing technology rather than disrupting it. Hence, to increase the predictability of an expected outcome of a research project, managers can concentrate a firm's resources on fewer technological areas, reducing the information asymmetry with the market and making outcomes more predictable.

These arguments support the idea that managers under earnings pressure are incentivized to reallocate resources into fewer diversified technological areas to achieve scale and learning (i.e., reducing the waiting time), and make research efforts more coherent and comprehensible (i.e., improve predictability). Thus, I formulated the following hypothesis:

Hypothesis 2 (H2). *An increase in earnings pressure induces a lower level of technological diversification in corporate innovation.*

Consequences for Innovation Quality

Earnings pressure, inducing an innovation approach favoring fewer but more well-known and more mature technologies, in the longer term translates into lower quality.

The first reason is related to the reduced use of basic science. Reliance on scientific knowledge has been found to affect the innovation performance of inventors positively, especially when combining diversified independent pieces of knowledge. For instance, reliance on science improves inventors' searches for more useful combinations (Fleming & Sorenson, 2004). Similarly, using science literature in innovation moderates the loss in value when exploring new fields (Arts

& Fleming, 2019). Experimentation with novel, emerging, and pioneering technologies and the use of scientific knowledge are also identified as sources of technological breakthroughs (Ahuja & Lampert, 2001; Fleming, 2002).

The second reason concerns the narrower knowledge base. Firms tend to create a broader knowledge base (Dosi, 1988; Nelson & Winter, 1982) than what they utilize (Gambardella & Torrisi, 1998; Patel & Pavitt, 1997). Expanding the range of different research activities can provide various types of benefits (Breschi et al., 2003). By building technological competences in enough fields, firms can build absorptive capacity to accommodate changes (Cohen & Levinthal, 1990) and spot opportunities and shifts in the market (Levinthal & March, 1993). This ability helps the generation of capabilities and cognitive frameworks that facilitate moving beyond local searches (Nelson & Winter, 1982) and enhance the creation of novel solutions (Schumpeter, 1947). For instance, technological diversification has been found to improve the identification of a higher number of possibilities to apply inventions (Novelli, 2015). A broader knowledge base achieved through technological diversification can improve innovation performance by facilitating the cross-pollination of ideas and enabling resource sharing across areas (Ahuja & Lampert, 2001; Miller et al., 2007). Investment in widespread technological areas enhances those absorptive capabilities that help companies assimilate external information (Garcia-Vega, 2006; Quintana-García & Benavides-Velasco, 2008). Finally, highly successful innovation outcomes are a function of opportunities for collaboration and the recombination of knowledge (Singh & Fleming, 2010). If a high-quality idea exists, firms with more diversified knowledge bases are best placed to spot and capture it. Therefore, I formulated the following hypothesis:

Hypothesis 3 (H3). *An increase in earnings pressure induces a lower level of quality in corporate innovation.*

METHOD

To test my hypotheses, various endogeneity concerns must be considered. First, merely comparing firms between capital markets with diverse levels of earnings pressure can be misleading since various unobservable market features or countries' institutional and regulatory environments can affect a firm's innovation decisions. Moreover, firms belonging to different capital markets can have intrinsically dissimilar characteristics. Second, examining a firm's cross-sectional consequences regarding variations in levels of earnings pressure within the same capital market can also lead to distorted results. Comparing differences in the innovation characteristics of the same firms before and after a change in the levels of earnings pressure does not prevent the possibility that other unobservable trends and time effects could alter those innovation characteristics. To overcome these issues, I applied an estimation model with a DID approach (Bertrand, Duflo, & Mullainathan, 2004).

Taking inspiration from economics and accounting research, I measured variations in earnings pressure derived from the frequency of reporting (Ernstberger et al., 2017; Fu et al., 2020; Gigler et al., 2014; Kraft et al., 2018). To identify the effect of interest, I exploited an exogenous change in firms' earnings pressure caused by a shift in the firms' regulatory environment. Specifically, I identified the TD of 2004 (Christensen, Hail, & Leuz, 2016; Leuz & Wysocki, 2016) as a promising "quasi-experimental" setting already applied in accounting literature to investigate the causality effect in real activities' manipulations as a consequence of reporting frequency (Ernstberger et al., 2017). First, this setting enables the identification of a group of treated firms with a similar group of European firms that did not change after the TD. Second, the longitudinal nature of the data allows the use of the DID specification to reduce endogeneity concerns. Third, the adoption of the new regulation happened at different points in time for different stock markets. This allows the construction of a staggered longitudinal sample that reduces even further the possible alternative explanations related to other phenomena happening in the same period.

Empirical Setting: Exogenous Change in Earnings Pressure. The TD is a European Union (EU) directive (2004/109/EC), a legal act of the EU requiring member states to achieve a particular regulatory objective. The TD was first emanated in 2004, establishing various rules to harmonize firms' information within capital markets in Europe. The TD required stock markets in member states to adopt mandatory quarterly reporting. Prior to the TD, the reporting frequency requirements differed across countries, either on a semiannual or quarterly basis. According to the TD, those stock markets for which quarterly reporting was not already mandatory were required to make firms issue Interim Management Statements (IMSs) for the first and third quarters. The regulatory changes in each stock market were adopted in a staggered fashion between January 2007 and April 2009.

I considered as a treatment group for my DID design those firms in stock markets that adopted IMSs on a quarterly basis, having previously being reporting semiannually. In this way, the introduction of the mandatory quarterly reporting in various EU stock markets, via the adoption of the TD, corresponds to an exogenous shock, aggravating earnings pressure. At the same time, I considered as control group those firms in stock markets with mandatory quarterly reporting already in place through local state regulations before the TD, thus not experiencing the exogeneous shock induced by the adoption of the TD. Therefore, it is expected that firms in control group had, before the adoption of the TD, a level of earnings pressure higher than the firms in the treatment group. After the adoption of the TD, both groups are under the same reporting frequency regime. If the earnings pressure induced by the adoption of the TD has consequences for firms' corporate innovation, I expected to observe a change in the differences between firms in the treatment and control groups after the regulatory change. For this study, I compared firms' innovation outcomes in the four years before the treatment (i.e., adoption of the TD) with different post-treatment time windows of four, five, and six years after the regulatory change. Appendix A reports additional discussion on the empirical setting and details on the composition of the treatment and control group.

Data. I initially collected financial data from the Compustat Global database, identifying firms listed in EU-15 primary stock markets operating in manufacturing (NAICS 31-32-33). Factset databases provide data on firms' ownership. Regarding patents, I used the PATSTAT data on European patents. The matching between PATSTAT assignee codes and company identifiers is in the Orbis Burau Van Dijk database. From 2,233 companies identified in the Compustat Global database between 2003 and 2014, for which I found matches on Orbis, 425 had at least one patent application within the time window. Of these, 373 had at least one granted patent application, allowing me to calculate my dependent and control variables. In this way, including missing values in some variables of interest, I obtained a sample of 2,053 firm-year observations for an eight-year window.[4]

Dependent Variables. *Scientific Intensity* is calculated by considering the stock of a firm's patents containing scientific knowledge, as percentage of patents applications citing a journal publication. *Technological Diversification* is measured using the portfolio diversification among technological areas, calculated by entropy index (Granstrand & Oskarsson, 1994; Kim, Lee, & Cho, 2016; Miller et al., 2007; Robins & Wiersema, 1995).[5] *Innovation Quality* is

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[4] Missing values of R&D were treated by substituting those missing with 0 and ROA with the industry-year mean. Dummy controls for the substitution were added in these cases.

[5] I computed the *Scientific Intensity* using a four-years moving average of the percentage of a firm's patent applications citing journal publications in each year, with decreasing weights (0.4 for *t,* 0.3 for *t-1,* 0.2 for *t-2,* 0.1 for

calculated in two ways. *Average Quality* is the natural logarithm (plus one) of the number of forward citations to granted patent applications, adjusted by technological class and year. In a related way, *Innovation Breakthroughs* considers the percentage of patents that have achieved a particular significant success. This factor is important because citations are greatly skewed, and the mean might not necessarily be revealing of the phenomenon. *Innovation Breakthroughs* are rare events characterized by extreme attributes of novelty and radicality (Fleming, 2002, 2007; Kelley, Ali, & Zahra, 2013). They are measured as the firm's percentage of granted patent applications being in the top 5% of forward citations in a specific technological class and year (Kaplan & Vakili, 2015; Singh & Fleming, 2010). A negative effect on both measures suggests that firms suffer in the longer term, not just for a downward mean shift in the quality of their innovation output, but also with a lower probability of achieving extremely successful outcomes.

Independent Variable and Estimation Procedure. The DID approach (Bertrand, Duflo, & Mullainathan, 2004) aims at identifying the effect of the exogenous change in earnings pressure by comparing the difference in outcomes before and after the change across the

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t-3). Similarly, I computed the *Technological Diversification* entropy index considering the granted patent applications in a focal year in addition to three previous years, and I weighted each year with a decreasing weight (0.4 for *t*, 0.3 for *t-1*, 0.2 for *t-2*, 0.1 for *t-3*). This computation is supposed to be less sensitive to volatile changes in patenting activity and should capture a larger stock of knowledge base, assigning lower weight to those older patents since those research activities in the past that generated those older patents are today probably less relevant, applicable, or even dismissed. In other words, this measure includes the contribution of older research activities in shaping today's knowledge base, but with decreasing importance. Results are consistent using different ranges of the time window. Following a broad range of literature (Breschi et al., 2003; Huang & Chen, 2010; Kim et al., 2016), in this study I identify as technological areas those technological subclasses reported in patent applications via the International Patent Classification (IPC), considered at the four-digit IPC level, resulting in a total number of technological areas of N=623.

treatment group and a control group. Therefore, the comparison concerns whether the difference in the dependent variables of treated firms, before and after the regulatory change, differs from the difference in the dependent variables of other control firms. In other words, firms are directly compared with themselves before and after the introduction of mandatory quarterly reporting. To estimate the effect of an exogenous change in earnings pressure induced by introducing mandatory quarterly reporting, the estimation model is:

$$DV_{i,t} = [FE_i] + [FE_t] + \beta_A Treated_i * Post\_Treatment_t + \beta_X X_{i,t} + \epsilon_{i,t}$$

$Treated_t$ is a dummy variable that equals 1 if the firm *i* is in a stock market that experienced the regulatory change imposed by the TD. $Post\_Treatment_t$ is a dummy variable equal to 1 in years following the year of regulatory change (adoption of the TD). The coefficient β_A of the interaction $Treated_i * Post\_Treatment_t$ constitutes the effect I aim to estimate. It captures the variance in the dependent variables that is generated by the treatment (introduction of mandatory quarterly reporting). This interaction is equal to 1 if a firm is in the treatment group and the years occur after the regulatory change. Firm fixed effects (FE_i) capture systematic differences between the treatment and control groups, while year fixed effects (FE_t) control for time variant characteristics. Finally, $X_{i,t}$ is the vector of control variables for each firm *i* in year *t*.

Control Variables. To improve the rigor of my estimation, I added the estimation model of firms' observable characteristics to provide a better control for unobserved heterogeneity and other confounding factors that can cooccur in the treatment. I added firm *Size*, measured in the natural logarithm (plus one) of a firm's assets, and a firm's *Return on Assets* to control for performance. To control for any possible managing costs effect (to observe the effect on the innovation output *given* the level on innovation expenditures), I also added *R&D Stock*, computed as the natural logarithm (plus one) of the stock of R&D, considering R&D investments in three years (*t, t-1, t-2*), with an annual depreciation of 15% (Hall, 1993). Since I want to identify the effects on type and quality of innovation, it is also necessary to control for the sheer overall innovation output. Therefore, I added *Number of Patents*, measured as the natural logarithm (plus one) of a firm's patent applications, adjusted for technology and year. Additionally, the level of specialization in a core-technological area can determine how many competences and capabilities a firm has developed around the most crucial technology, affecting the incentives to reallocate resources in a more or less risky or diversified portfolio of research areas. Thus, the estimation model includes the variable *Core-Technology Capabilities*, measuring the firm's comparative advantage in a technological area.[6] Regarding a firm's financial characteristics, I added *Debt-to-Equity Ratio* to control for possible financial distress that can cause a change in the research efforts. Moreover, I considered the *Tangibility Ratio* to address the type of unobserved heterogeneity across firms related to the nature of the assets, and *Payout Ratio* to control for a firm's intrinsic propensity to invest the bulk of its earnings into future growth opportunities. Regarding capital market characteristics, since the adoption of TD might have attracted different types of shareholders, bringing different levels of impatience, I controlled for the firm's level of *Institutional Ownership* measured as shares of total market capitalization. I controlled also for time-invariant unobserved heterogeneity at the firm's level by using a multiple high-dimensional fixed effects model absorbing fixed effects that relate to firms, and time

[6] This is computed using the revealed technology advantage (RTA; Patel and Pavitt, 1997), comparing the patent share for the technological area with the firm's overall share of patent applications across the entire technological area. The measure (Patel & Pavitt, 1997; Kim et al., 2016), considers the maximum value among a firm's various RTA indices in each of the technological area (i.e., relative strength) multiplied by the count of granted patent applications in that specific technological area (i.e., absolute strength).

variant characteristics using years' fixed effects, allowing for clustered standard errors (Correia, 2017). Finally, given the longitudinal nature of the data, I clustered standard errors on stock markets and years to allow for intragroup correlation.

Table 1 reports the descriptive statistics and correlations. From this table, it is evident how the treatment dummy is not strongly correlated with any other regressors, suggesting the there is a low heterogeneity among the treatment and control group.

-INSERT TABLE 1 ABOUT HERE-

RESULTS

This section reports my empirical results. I first assess the effect of the exogenous change in earnings pressure on corporate innovation type and quality. Second, I provide different robustness tests confirming the results. Finally, I discuss and verify the mechanisms through which these effects occur.

The Consequences of an Exogenous Change in Earnings Pressure

To begin, I report binned scatter plots displaying the average values of *Scientific Intensity* and *Technological Diversification* before and after the year of introduction of the regulatory change, comparing treated firms (that is, firms experiencing the introduction of the mandatory quarterly reporting) and the control group (that is, firms already under the mandatory quarterly reporting regime). Figure 1 reports suggestive evidence that in periods before the introduction of the mandatory quarterly reporting, treated firms, while displaying parallel patterns to the control firms, reported consistently higher levels of *Scientific Intensity*. This finding is in line with the proposed idea that those firms in the treatment group, being under a semiannual reporting regime, experiencing a lower level of earnings pressure before the treatment. However, in periods following the change in the reporting frequency, the treated firms experienced a decrease in the average value of *Scientific Intensity* to a level similar to the firms in the control group. Similarly,

Figure 2 reports the same phenomenon for the level of *Technological Diversification*. This evidence provides support of earnings pressure consequences on corporate innovation. It suggests that firms in stock markets without mandatory quarterly reporting were experiencing a higher level of *Scientific Intensity* and *Technological Diversification.* However, after the regulatory change, this difference is lost, since treated firms are now under the same regulatory regime of the control group (i.e., they are experiencing a similar level of earnings pressure).

--- INSERT FIGUREs 1 AND 2 HERE ---

In the OLS regressions of Table 2, my results confirm the expectation about the lower degree of scientific intensity and technological diversification generated from an increased earnings pressure. Model 1.1 reports a negative, significant difference between the treatment and control firms, before and after the treatment, in *Scientific Intensity* (β = -0.015, p = 0.002). Considering the mean of the scientific intensity for the treated group before the treatment being equal to 0.049, earnings pressure accounts for a 31% decrease (0.015/0.049). Model 1.2 displays the effect in the long term, with an expanded time window of +6 periods from the treatment. The effect is persistently negative and significant, with no particular changes, suggesting that the change is structural, and once initiated remains persistent through the following years. Model 1.3 displays a negative, significant difference between the treatment and control firms, before and after the treatment, in *Technological Diversification* (β = -0.207, p = 0.001). Considering the mean of technological diversification for the treated group before the treatment is 2.63, earnings pressure accounts for 7.9% decrease (0.207/2.63). Model 1.4 reports the effect in the long term, with an expanded time window of +6 periods from the treatment. Even in this case, the effect is persistently negative and significant, with slightly greater magnitude (8.4% decrease).

--- INSERT TABLE 2 ABOUT HERE ---

Table 3 reports the effects on *Average Quality* and *Innovation Breakthroughs*. As expected, consequences on the quality of innovations appear in the longer term. Model 2.1 displays no significant difference in the *Average Quality* of innovation between the treatment and control firms in the first four time periods, whereas it becomes significant (β = -0.205, p = 0.012) when considering the expanded time window. Similarly, innovation quality in terms of *Innovation Breakthroughs* reports a significant, negative difference between treatment and control firms after four time periods (β = -0.036, p = 0.022). Therefore, in the long term, the earnings pressure effect accounts for a 22% decrease in *Average Quality* (0.205/0.95) and a 75% decrease in the likelihood of *Innovation Breakthroughs* (0.036/0.048).

--- INSERT TABLE 3 ABOUT HERE ---

To detect the dynamics affecting the different periods, Table 4 replicates the results that display the effect of the treatment in the short-, medium-, and long run using a dummy for each period. The decline of the level of scientific intensity is stronger in the short term, but it is also short-lived. Technological portfolio diversification is, instead, a structural change in the innovation activities that occur in the short term and is consistently maintained at the same reduced level. The decline of the innovation average quality and the percentage of breakthroughs is confirmed as an effect that occurs in the longer term, being particularly substantial and significant only four years after the treatment.

--- INSERT TABLE 4 ABOUT HERE ---

Finally, despite my DID approach reduces the risk of having potentially biased estimates due to endogeneity being generated by underlying firms or market characteristics, in Appendix B I provide additional specifications and robustness tests to strengthen my results. Among others, I ran the same regressions of the main models using a restricted sample with firms matched based on observable characteristics, and the results are confirmed and significant (Table B in Appendix B).

Investigating the Mechanisms

Having provided substantial empirical evidence for the consequences of earnings pressure on corporate innovation in terms of managing revenues (affecting type and quality of innovation outcome), I now explore the possible underlying mechanisms.

Cost of Waiting. If earnings pressure induces greater incentives for increasing the speed to deliver results, this should be more evident when the cost of waiting is higher, such as when firms are underperforming and the risk to a manager (e.g., of getting fired) is perceived as more imminent. In this case, I expect the incentives to lower the waiting time of the innovation results to be higher (lower) in firms that have worse (better) performance. Results (Table C1 in Appendix C) confirm that the negative effect of earnings pressure on scientific intensity and technological diversification is present for those firms performing worse than their industry peers, whereas no particular differences are observed in the longer-term effect on innovation quality.

Predictability. If earnings pressure makes managers more inclined to smooth predictable results, this should be truer regarding the more investors and the capital market expect stable returns. In more stable industries, surprising negative results would conflict with market expectations, causing a higher risk of devaluation of the stock price. Firms in those stable industries should then have higher incentives to lower information asymmetry with the market and increase predictability. To test this, I examined differences in industry volatility. As expected, the short-term negative effect on technological diversification and the long-term decline of innovation quality and breakthroughs are all stronger for firms in more stable industries (Table

C2 in Appendix C). However, the effect on the decline of scientific intensity appears to be less subject to industry volatility.

Related and Unrelated Diversification. Since earnings pressure creates incentives for quicker innovation results, managers should concentrate on those technological activities that most reduce friction and improve learning. Research activities that are more similar to each other should provide better opportunities to achieve them. Technological relatedness is associated with the level of similarity of the knowledge base. The more related the technological knowledge base, the more quickly the knowledge can be assimilated and exploited (Cassiman, Colombo, Garrone, & Veugelers, 2005; Cohen & Levinthal, 1990). The assimilation and application of the new combined knowledge of unrelated knowledge bases is difficult, resource consuming, and can also be counter-productive (e.g., Haspeslagh & Jemison, 1991). If a manager perceives pressure to deliver quicker results, the opportunity costs of keeping resources and capabilities separated are higher the more similar they are, as knowledge similarity and common practices and routines can be better exploited. However, the opposite can also happen: since earnings pressure creates incentives for more predictable innovation results, managers should concentrate on those technological activities that better reduce uncertainty. If this is the case, distant and unrelated research efforts are those that should be redeployed. To explore which of the two mechanisms plays a stronger role in the decline of technological diversification, I exploited the fact that the entropy index of technological diversification is additive and, thus, it is possible to deconstruct it into the sum of related and unrelated diversification (Jacquemin & Berry, 1979; Palepu, 1985). Related technologies are those within the same macro-area (two digit), whereas unrelated diversification measures the spread of technologies between different macro-areas. The results (Table C3 in Appendix C) reveal that effect is driven by related (Model 6.1: $ß = -0.189$, $p = 0.000$) instead of unrelated diversification (Model 6.2: $ß = -0{,}018$, $p = 504$). This suggests that the cost-of-waiting mechanism plays a greater role in explaining reduction in the technological diversification as a response to an increase in earnings pressure. Moreover, given the non-significant change in unrelated diversification, this also suggests that earnings pressure does not lower the propensity for exploration relative to exploitation; that is, searching unrelated, distant knowledge. Instead, the effect of earnings pressure appears to be related to a reshape of the diversification structure of the searched alternatives, rather than the explorative vs exploitative direction of the efforts. In other words, earnings pressure appears changing where to search for alternatives (i.e., the structure of the portfolio; thus, how many alternatives are in place) but not altering the explorative search for new alternatives (i.e., the search for novel alternatives).

Non-granted Patent Applications. If it is true that firms concentrate research efforts by pooling resources and research efforts into fewer projects, each research and development stream of activities can benefit from greater resources available to experiment with, test the alternatives, and superior learning, leading to better knowledge of the fields. Therefore, the standards and benchmark requirements for novelty, usefulness, and not-obviousness should be better understood. It follows that, on the bright side, in the fewer well-known areas one can expect a lower number of wasted innovation attempts. Conditional to applying for a patent, results confirm a higher probability that the proposed patent meets the patentability criteria following the exogenous change in earnings pressure (Table C4 in Appendix C). Although there is a slight decline of the granted patents (Model 7.1: $\beta = -0.003$ $p = 0.109$), confirming some of the previous literature findings (e.g., Fu et al., 2020), non-granted patents appear to have a much stronger and significant decline (Model 7.2: $\beta = -0.009$, $p = 0.000$), which is consistent across different model specifications. Figure C1 in Appendix C illustrates the temporal distribution of this effect.

Governance Matters. Corporate governance can play a crucial role in a firm's ability to innovate, alleviating agency problems that induce myopic managerial behaviors (Keum 2020).

Ownership concentration is a source of power (Salancik & Pfeffer, 1980) that can act as a corporate governance mechanism to reduce agency costs associated with manager–shareholder conflicts (Villalonga & Amit, 2006). A higher concentration of corporate ownership alleviates agency conflicts of interest between owners and managers, having a positive effect on innovation (Baysinger, Kosnik, & Turk, 1991; Francis & Smith, 1995). In the context of this study, it is possible to leverage my empirical setting to observe how ownership concentration can differently affect firms' responses to earnings pressure. In terms of scientific intensity, higher-concentrated ownership can alleviate agency concerns and ease the incentives to increase predictability. However, the opposite can also happen. Higher-concentrated investors have a large proportion of their wealth locked up in the firm. Agency assumption that owners can diversify their portfolio with investment outside the firm is less plausible, and this might change their keenness for risk-taking (Wright, Ferris, Sarin, & Awasthi, 1996). Since larger investors cannot easily exit from their investment, they have higher interests in influencing managerial decisions because of their large stakes in the firm's capital (Auvray & Brossard, 2012; Holmström & Tirole, 1993). Therefore, higher-concentrated ownerships can escalate (instead of mitigating) the effects of earnings pressure to reduce most risky innovation activities and, thus, increase the predictability of the results. Results for this test are reported in Table C5 in Appendix C. Model 8.1 illustrates that the effect on the reliance on basic science is in line with the latter argument, with higher ownership concentration being associated with a stronger decline of scientific intensity. In terms of technological diversification, the consequences are different. In this case, the two motives point in the same direction. Higher ownership concentration can alleviate agency concerns and, thus, reduce the effect of earnings pressure on technological diversification. Similarly, since higher-concentrated firms are associated with larger undiversified investors, they are also less willing to reduce their diversification even further into fewer technological areas. In line with both these reasons, Model 8.2 confirms that firms with higher ownership concentration display no changes in their technological portfolio diversification as a response to earnings pressure.

Managing Costs. The focus of this study is to identify the innovation consequences of earnings pressure in terms of managing revenues. I argued that the repercussions of earnings pressure in terms of managing costs does not necessarily impact corporate innovation. In this paragraph, I check whether, according to my setting, earnings pressure has a managing cost effect on firms' innovation expenditures (i.e., whether it induces a change in R&D input). My data suggest the absence of a managing cost effect on R&D expenditure and the existence instead of an R&D legitimacy effect (Ahuja & Novelli, 2017; Bebchuk & Stole, 1993; Tinn, 2010). Ahuja and Novelli (2017) argue that R&D investments are susceptible to overinvestment because of the high level of legitimacy associated with them. This issue is caused because R&D is usually recognized as socially legitimate, a repository of good investments, and a signal of good management (Tinn, 2010). Various studies have reported that R&D investments are associated with stock overpricing (Perez, 2003; Polk & Sapienza, 2008). Since investments in R&D are easily observable and measurable (Bebchuk & Stole, 1993), it could be expected that managers might respond to earnings pressure by signaling good management through higher R&D expenditure. Even if not significant, the results of this study reveal an increase in R&D investments for treated firms after the increase in reporting frequency (Table C6 in Appendix C). To explore whether this change is driven by a legitimacy effect, I investigated the moderating effect of ownership concentration and industry R&D intensity. Ahuja and Novelli (2017) point out two factors that emphasize the tendency of R&D legitimacy: first, R&D is even more legitimized for firms operating in R&D intensive environments; and second, R&D is even more legitimized for firms with higher-concentrated ownerships, since high-concentrated owners might consider R&D investment as an “option” to diversify. My data confirm these predictions. Firms in R&D-intense industries tend to increase their R&D investments as a response to earnings pressure, whereas those in industries with a low use of R&D decrease their investment level since it is not suitable as signal of good management. This dissimilarity escalates for higher levels of ownership concentration (Figure C2 in Appendix C).

DISCUSSION AND CONCLUSION

In this study, I argued that earnings pressure induces managers to achieve quicker and more reliable innovation results (i.e., managing revenues), which has consequences for innovation type and quality. I tested this prediction by using a particular empirical setting that enabled me to exploit an exogenous change in the regulation regarding the mandatory reporting frequency. The EU TD established that EU stock markets must adopt mandatory quarterly reporting from 2007 (with some exceptions from 2008 and 2009). I applied a DID approach to compare firms in stock markets that changed from semiannual to quarterly reporting (increasing their reporting frequency and, thus, their earnings pressure) with firms in a control group in those stock markets in which mandatory quarterly reporting was already in place due to country-level regulations. The empirical setting of this study provided an interesting opportunity to disentangle the causality behind earnings pressure and its possible consequences. My results offer various implications.

First, increased pressure for immediate results incentivizes managers to lower the search in most uncertain terrains, such as basic sciences, and to reduce the scope of the search, which have repercussions on patents’ future impacts. These consequences on corporate innovation are not driven by managers reacting to earnings pressure by managing costs, but instead by managing revenues. Overall, earnings pressure alters firms’ innovation approaches, not how much they invest in them. By changing how they innovate, firms produce more mature innovations in fewer but better-known areas and, consequently, with lower quality. This mechanism is, ultimately, how earnings pressure can inhibit corporate innovation.

Second, despite a vast number of empirical investigations on the consequences of earnings pressure on innovation, the lack of alignment of these studies' results reflects a limited and superficial theoretical understanding of the mechanisms behind the observed effects. This study reveals the reasons earnings pressure can translate into innovation consequences. Although most of the existing research efforts consider consequences of earnings pressure from the standpoint of managing costs, I distinguished a novel channel—managing revenues—that has been overlooked by the literature. I corroborated my theoretical explanations by finding support for the proposed mechanisms that make managing revenues a response to earnings pressure: *cost of waiting* and *predictability*. The results seem affected by the volatility of the performance and the level of the performance compared with the industry peers. The lower the performance, the more urgent it is for managers to deliver results. The more stable the performance of an industry, the more investors expect stability in the results and, thus, managers are more incentivized to prefer predictability.

Finally, my results also suggest possible "bright sides" of managing revenues as a consequence of earnings pressure. I found that firms tend to become more effective in the patent application process, suggesting that they are working on technological areas in which better knowledge and experience exist. This approach leads to fewer wasted innovation resources, lowering the number of patents that do not meet the patentability requirements. This speaks to the literature suggesting efficiency consequences of earnings pressure. At the same time, this finding provides interesting evidence suggesting that the commonly believed negative repercussions of earnings pressure on sheer innovation quantity are, instead, associated with a decrease in wasted (non-granted) innovation output.

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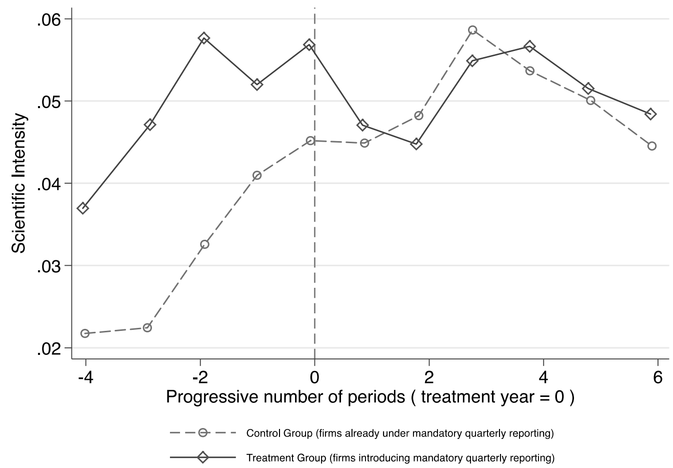
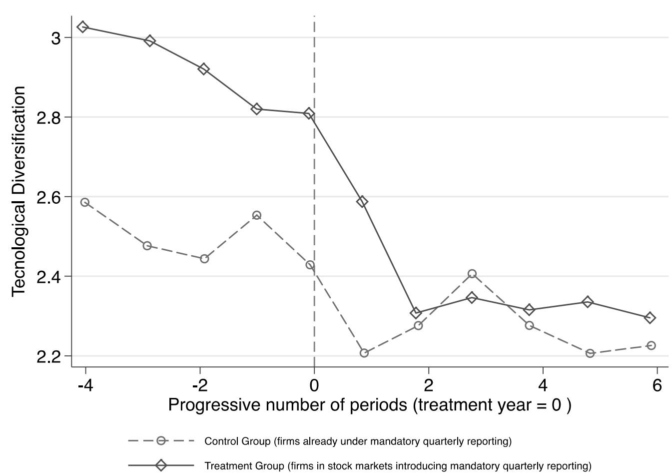
Figures and Tables

FIGURE 1 Average *Scientific Intensity* by treatment and control group



Notes: Each point corresponds to a binned scatterplot controlling for R&D stock and industry fixed effects. Eleven bins are calculated, one for each period. Period = 0 for treatment year (i.e., the year of introduction of the mandatory quarterly reporting). Periods > 0 correspond to years after the treatment.

FIGURE 2 Average *Technological Diversification* by treatment and control group



Notes: Each point corresponds to a binned scatterplot controlling for R&D stock and industry fixed effects. Eleven bins are calculated, one for each period. Period = 0 for treatment year (i.e., the year of introduction of the mandatory quarterly reporting). Periods > 0 correspond to years after the treatment.

TABLE 1 Summary statistics and correlations

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 Post Treatment	0.56	0.50																
2 Treated	0.83	0.38	-0.02															
3 R&D Stock[a]	3.84	2.46	0.14	-0.03														
4 Size[b]	7.15	1.87	0.05	0.05	0.66													
5 Institutional Ownership (%)	0.22	0.16	0.05	-0.20	0.38	0.35												
6 Debt-to-Equity	0.57	10.50	0.00	0.00	0.02	0.02	0.00											
7 Tangibility Ratio	0.25	0.14	-0.09	0.10	-0.26	0.03	-0.14	-0.07										
8 Payout Ratio	0.35	2.29	-0.01	-0.03	0.04	0.03	0.06	0.00	-0.02									
9 ROA	0.04	0.09	-0.05	0.00	0.06	0.12	0.12	-0.07	-0.02	0.02								
10 Core-Technology Competences	5.00	2.12	-0.03	-0.06	0.42	0.38	0.18	0.00	-0.02	0.04	0.10							
11 Number of Patents[c]	0.03	0.07	-0.01	-0.01	0.44	0.43	0.18	0.00	-0.06	0.00	0.06	0.48						
12 Number of Granted Patents[e]	0.03	0.07	-0.01	-0.02	0.43	0.42	0.17	0.00	-0.07	0.00	0.07	0.49	0.98					
13 Technology Diversification	2.53	1.88	-0.05	0.02	0.50	0.44	0.20	0.01	0.00	0.05	0.05	0.68	0.44	0.43				
14 Science Intensity	0.05	0.10	0.04	0.04	0.21	0.09	0.05	0.00	-0.05	-0.01	-0.04	0.19	0.12	0.10	0.15			
15 Number of Non-Granted Patents[d]	0.02	0.08	0.00	0.00	0.43	0.43	0.18	0.00	-0.04	0.01	0.05	0.44	0.98	0.93	0.42	0.12		
16 Average Quality	0.89	0.92	-0.05	0.03	0.41	0.26	0.19	0.00	-0.10	0.01	0.07	0.59	0.40	0.41	0.58	0.10	0.36	
17 Breakthroughs (%)	0.05	0.12	0.04	-0.02	0.12	0.03	0.09	0.00	-0.10	0.02	-0.05	0.04	0.03	0.03	0.02	0.02	0.03	0.42

[a] ln(1+R&D Stock)

[b] ln(1+Assets)

[c] ln(1+Adjusted Number of Patents)

[d] ln(1+Adjusted Number of Granted Patents)

[e] ln(1+Adjusted Number of Non-Granted Patents)

TABLE 2 Difference-in-differences regression results for H1 and H2 [a, b]

	Scientific Intensity		Technological Diversification	
	(1.1)	(1.2)	(1.3)	(1.4)
Treated * Post Treatment	**- .015**	**- .013**	**- .207**	**- .221**
	(.005)	**(.005)**	**(.058)**	**(.063)**
R&D Stock	- .003	- .002	- .027	- .006
	(.002)	(.002)	(.019)	(.020)
Number of Patents	.075	- .006	.075	.303
	(.057)	(.068)	(.929)	(.756)
Core-Technology Capabilities	**.009**	**.010**	**.318**	**.360**
	(.002)	**(.002)**	**(.033)**	**(.023)**
Size (Assets)	.005	.004	**.287**	**.218**
	(.006)	(.005)	**(.075)**	**(.067)**
Return on Assets	.028	- .002	- .390	- .271
	(.025)	(.023)	(.277)	(.226)
Institutional Ownership	- .018	.004	- .363	- .435
	(.014)	(.014)	(.293)	(.268)
Debt-to-Equity [c]	- .027	- .025	.012	.080
	(.021)	(.021)	(.125)	(.152)
Tangibility	- .031	- .025	.624	**.935**
	(.043)	(.039)	(.315)	**(.337)**
Payout Ratio	- .002	- .002	.011	.006
	(.001)	(.001)	(.012)	(.014)
Time Window	-4 +4	-4 +6	-4 +4	-4 +6
Observations	2,035	2,514	2,035	2,514
R-squared	0.772	0.756	0.920	0.904

[a] Bold type indicates that the coefficient estimate differs significantly from zero with 95% confidence
[b] Standard Error in parentheses, clustered by stock market and year
[c] Coefficients multiplied by 100

TABLE 3 Difference-in-differences regression results for H3 [a, b]

	Average Quality		% of Breakthroughs	
	(2.1)	(2.2)	(2.3)	(2.4)
Treated * Post Treatment	- .089	**- .205**	- .031	**- .036**
	(.071)	**(.080)**	(.018)	**(.016)**
R&D Stock [c]	.004	.095	.264	.045
	(.192)	(.173)	(.236)	(.240)
Number of Patents	**1.668**	**2.259**	**- .190**	**- .163**
	(.801)	**(.890)**	**(.066)**	**(.068)**
Core-Technology Capabilities	**.147**	**.162**	**.014**	**.016**
	(.021)	**(.017)**	**(.006)**	**(.006)**
Size (Assets)	.066	.036	- .015	- .006
	(.059)	(.054)	(.010)	(.010)
Return on Assets	- .2	- .166	.038	- .004
	(.224)	(.225)	(.090)	(.078)
Institutional Ownership	.072	.180	.001	.033
	(.227)	(.213)	(.049)	(.040)
Debt-to-Equity [c]	- .205	- .069	.024	.016
	(.266)	(.203)	(.015)	(.014)
Tangibility	.087	- .038	.068	.008
	(.366)	(.364)	(.079)	(.084)
Payout Ratio [d]	.013	- .043	.004	.006
	(.127)	(.130)	(.008)	(.010)
Time Window	-4 +4	-4 +6	-4 +4	-4 +6
Observations	2,035	2,514	1,579	1,954
R-squared	0.708	0.678	0.373	0.351

[a] Bold type indicates that the coefficient estimate differs significantly from zero with 95% confidence
[b] Standard Error in parentheses, clustered by stock market and year
[c] Coefficients and Standard Errors multiplied by 100
[d] Coefficients and Standard Errors multiplied by 10

TABLE 4 Difference-in-differences coefficients estimation by different post-treatment time periods

	Short-Term Effects		Long-Term Effects	
	(3.1)	(3.2)	(3.3)	(3.4)
	Scientific Intensity	Technological Diversification	Avg. Quality	% Breakthroughs
Treated * Short-Term (+1/+2 Periods)	**- .014**	**- .207**	- .051	- .012
	(.005)	**(.061)**	(.070)	(.012)
Treated * Medium-Term (+3/+4 Periods)	**- .015**	**- .213**	**- .189**	**- .045**
	(.005)	**(.066)**	**(.087)**	**(.021)**
Treated * Long-Term (>+4 Periods)	- .010	**- .249**	**- .437**	**- .052**
	(.006)	**(.106)**	**(.099)**	**(.019)**
Controls	Yes	Yes	Yes	Yes
Observations	2,514	2,514	2,514	1,954
R-squared	0.756	0.904	0.680	0.353

[a] Bold type indicates that the coefficient estimate differs significantly from zero with 95% confidence

[b] Standard Error in parentheses, clustered by stock market and year

Appendix A: Empirical Setting

The Transparency Directive is a European Union (EU) directive (2004/109/EC) requiring member states to achieve a particular regulatory objective. I considered as a treatment group those firms in stock markets that adopted IMSs on a quarterly basis, having previously being reporting semiannually. As a control group, I considered those firms in stock markets with regulations in place before the TD requiring reporting on a quarterly basis. It is worth highlighting four important considerations.

First, the TD introduced other regulatory changes in addition to the mandate to issue IMSs (Christensen, Hail, & Leuz, 2016), such as notifications regarding shareholder rights and access to regulated information. A possible issue can arise if some of these other changes generate an effect in my dependent variable, confounding the actual effect of reporting frequency. However, this can hardly be the case since not only were most of the other regulations already in place in most EU countries in some form (Ernstberger et al., 2017), but also the treatment and control groups were constructed considering the state of reporting frequency regulation before and after the adoption. For any other concurrent changes to be misleading, they should have affected the distribution between treatment and control groups in the same exact way, which I argue is improbable.

Second, the years of adoption (2007–2009) coincide with the financial crisis period of 2007–2008. However, to believe that this could alter the interpretation of the results, the financial crisis must have impacted firms differently in those countries in the treatment and control groups. The firm-year fixed-effect estimation (detailed below) can quantitatively control for any yearly conditions of firms that can be related to the financial crisis, such as country GDP. I addressed any possible further concerns in the robustness tests.

Third, for the purpose of this study I only consider mandatory reporting. Voluntary reporting is not a useful instrument because, under a voluntary reporting regime, the decision to report information is, per-se, endogenous to a firm's conditions. In these terms, voluntary reporting should not provide any remarkable short-term pressure for earnings since there is no obligation to report bad news.

Finally, IMSs do not necessarily contain quantitative financial information. The TD set requirements to provide "an explanation of material events and transactions that have taken place during the relevant period and their impact on the financial position of the issuer and its controlled undertakings, and a general description of the financial position and performance of the issuer and its controlled undertakings during the relevant period" (EU, 2004). Since quantitative financial information can be considered as a more stringent requirement, with stronger consequences in terms of earnings pressure, a first possibility is to investigate as treatment only those firms that deliver quantitative information in the IMSs. However, this could result in a hazardous source of endogeneity in my model, since the decision to deliver financial information is voluntary and, thus, can be related to unobservable firm characteristics. Therefore, I considered in my treatment group all firms that changed to a quarterly basis, independently from the format (qualitative or quantitative) of the information. If any biases arose from this choice, they would be in the opposite direction of the main effect; thus, the significant differences between treatment and control group would be the lower bundle.

Table A reports the details of the treatment and control groups.

--- INSERT TABLE A ABOUT HERE ---

Appendix B: Robustness Tests

My DID approach reduces the risk of having potentially biased estimates due to endogeneity being generated by underlying unobservable firms or market characteristics. However, I provide additional specifications to strengthen my results.

First, I wanted to check if my empirical setting meets the parallel trends assumption of the DID approach. Figures 1B to 4B are graphs of the DID coefficients (expressed in terms of standard deviations) over the years before and after the regulatory change. None of the graphs reveal significant differences before 2007, confirming that the treatment and control group are on parallel trends before the treatment. For those short-term effects (decline in scientific intensity and technological diversification), the drop is observable starting from 2007. This suggests that some firms might have adjusted their innovation approaches in order to be ready to deliver quicker and smoother results as soon as the first year of regulatory change. Finally, the graphs confirm the longer-term consequences of earnings pressure, with the decline in the quality starting after 2010.

--- INSERT FIGURES 1B-4B ABOUT HERE ---

Second, one possible concern is related to the period of the treatment coinciding with the financial crisis. To control for this, I replicated the econometric analysis controlling for the Ohlson score of financial distress (Dowell, Shackell, & Stuart, 2011; Ohlson, 1980), finding consistent results. Moreover, I also used a restricted sample, including only firms that were consistently present in all the periods within the window to control for firms going bankrupt. Again, the results are confirmed (results available from the author).

Third, even if the described DID approach is commonly considered appropriate to mitigate endogeneity regarding pretreatment intrinsic differences between the treatment and control groups, to improve the comparability between firms in capital markets with previous semiannual reporting (treatment group) and those already under mandatory quarterly reporting (control group), I tested the robustness of my results by using a stringent group comparison. I created a new set, matching treatment firms to control firms with comparable pretreatment attributes. I matched firms based on observable indicators that can make them more similar, even if listed in different stock markets. Specifically, I performed coarsened exact matching (CEM, Iacus, King, & Porro, 2011) to build a matched sample based on four firms' characteristics (see Appendix A for additional details). Although matching procedures can reduce only those endogeneity biases attributable to observable features, meaning it is impossible to achieve a perfect match (Heckman & Navarro-Lozano, 2004), combining CEM with the previously discussed DID design is a robust method for providing evidence of causality (Azoulay, Stuart, & Wang, 2014; Singh & Agrawal, 2011). To increase the comparability of treatment and control groups, I matched firms based on observable characteristics before the treatment. Specifically, I performed Coarsened Exact Matching (CEM; Iacus, King, & Porro, 2011) using four criteria.

Retained earnings. This measure calculates the amount of net income left over after a firm has paid out dividends to its shareholders. Retained earnings are one of the main sources of internal founding for innovation (Caggese, 2012). In this context, I use them to capture the intrinsic propensity of a firm to be more or less oriented toward future growth opportunities. I divided firms into four bins based on their quartile values, with cutoffs at -1.38, -1.75, and 4.35.

Tobin's Q is computed as the market value of a company divided by its assets' replacement cost. This value estimates whether a company is overvalued or undervalued by the market to capture discrepancies in the ability of investors when valuing a firm's underlying assets and resources. I divided firms into four bins based on their quartile values, with cutoffs at 0.68, 1.19, and 2.14.

Capital expenditure. This measure enables a comparison of companies with similar propensities to undertake new projects or investments of different sizes. I divided firms into four bins based on their quartile values, with cutoffs at 0.9, 4.2, and 21.9.

Risk of Bankruptcy. I calculated the Ohlson score to compare firms that might have been affected by the financial crisis in the same manner. The Ohlson score has been used as a predictor of bankruptcy and a proxy for firm financial distress (Dowell et al., 2011; Ohlson, 1980). I divided firms into four bins based on their quartile values, with cutoffs at 0.42, 1.47, and 2.46.

Using this approach, I found respective matches for 228 out of 306 treated firms (and 62 out of 66 control firms), reducing the imbalance from 0.39 to 0.37. Table B the DID regressions using the restricted CEM sample, confirming consistent results.

--- INSERT TABLE B ABOUT HERE ---

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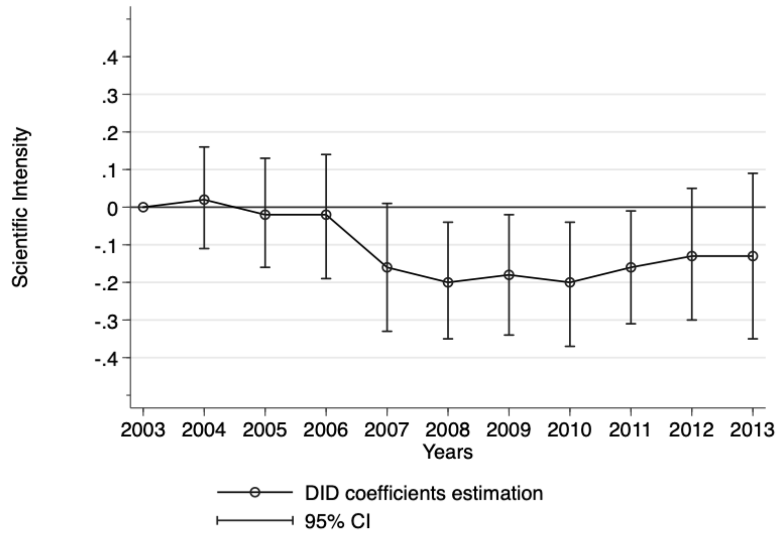
Table and Figures

TABLE A Treated and Control Groups

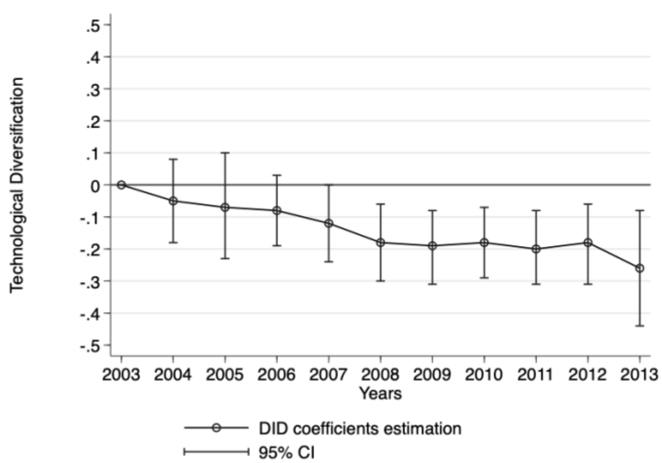
Stock Market	Country	Year of regulatory change	Treated Dummy	Nr. of Firms
Lisbon	Portugal		0	2
Athens	Greece		0	3
Stockholm	Sweden		0	30
Helsinki	Finland		0	31
NYSE Euronext Amsterdam	Netherlands	2009	1	15
Dublin	Ireland	2007	1	1
Vienna	Austria	2007	1	16
Copenhagen	Denmark	2007	1	20
NYSE Euronext Brussels	Belgium	2008	1	20
Deu Borse - Frankfurt	Germany	2007	1	37
London	United Kingdom	2007	1	46
NYSE Euronext Paris	France	2007	1	75
Deu Borse - IBIS	Germany	2007	1	76
			Total =	372

FIGURE B1 Difference-in-differences coefficients estimation of *Scientific Intensity* by year



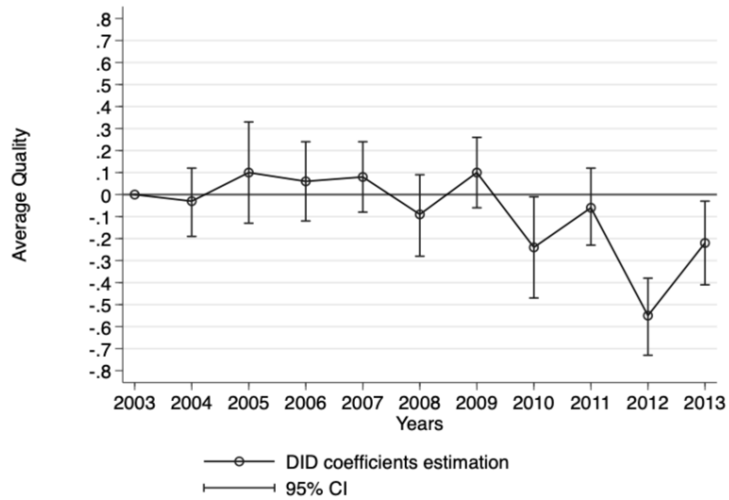
Notes: 2003 is set as a baseline. Values are reported in terms of percentage of the *Scientific Intensity* standard deviation of treated firms within the time window. A coefficient of - 0.1 corresponds to a drop of 10% of a standard deviation.

FIGURE B2 Difference-in-differences coefficients estimation of *Technological Diversification* by year



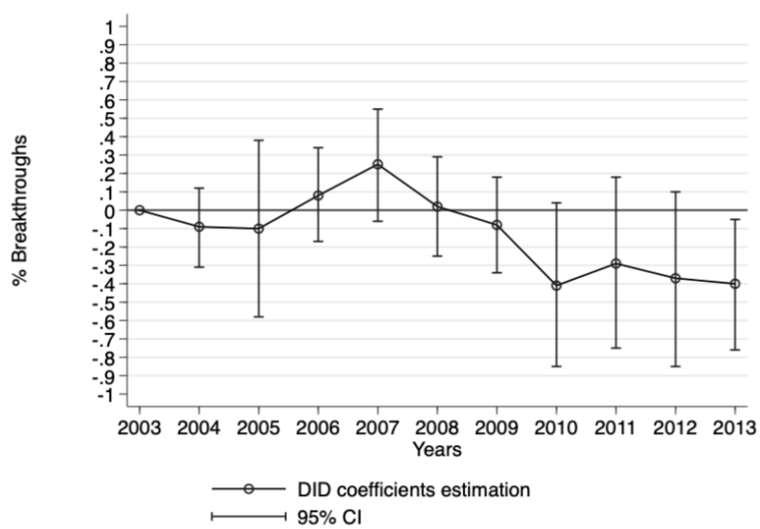
Notes: 2003 is set as a baseline. Values are reported in terms of percentage of the *Technological Diversification* standard deviation of treated firms within the time window. A coefficient of - 0.1 corresponds to a drop of 10% of a standard deviation.

FIGURE B3 Difference-in-differences coefficients estimation of *Average Quality* by year



Notes: 2003 is set as a baseline. Values are reported in terms of percentage of the *Average Quality* standard deviation of treated firms within the time window. A coefficient of - 0.1 corresponds to a drop of 10% of a standard deviation.

FIGURE B4 Difference-in-differences coefficients estimation of percentage of breakthroughs by year.



Notes: 2003 is set as a baseline. Values are reported in terms of percentage of the standard deviation of the probability of breakthroughs of treated firms within the time window. A coefficient of -0.1 corresponds to a drop of 10% of a standard deviation.

TABLE B Difference-in-differences regression coefficients with CEM sample.

	Short-Term Effects		Long-Term Effects	
	(1)	(2)	(3)	(4)
	Scientific Intensity	Technological Diversification	Avg. Quality	% Breakthroughs
Treated * Post Treatment	**- .019**	**- .206**	**- .187**	**- .035**
	(.006)	**(.063)**	**(.085)**	**(.015)**
R&D Stock	- .003	- .015	.006	.001
	(.002)	(.023)	(.020)	(.003)
Number of Patents	.099	- .347	**2 .843**	- .102
	(.065)	(.922)	**(.896)**	(.060)
Core-Technology Capabilities	**.009**	**.318**	**.153**	**.013**
	(.003)	**(.033)**	**(.018)**	**(.005)**
Size	.003	**.310**	.02[c]	- .007
	(.006)	**(.083)**	(.063)	(.011)
Return on Assets	- .023	- .167	- .336	- .042
	(.030)	(.285)	(.298)	(.077)
Institutional Ownership	- .026	- .545	.279	.011
	(.018)	(.307)	(.230)	(.044)
Debt-to-Equity [c]	- .028	.028	- .021	.013
	(.024)	(.119)	(.195)	(.015)
Tangibility	- .055	.508	.019	.017
	(.054)	(.428)	(.393)	(.083)
Payout Ratio	- .002	.012	- .003	.001
	(.001)	(.013)	(.013)	(.001)
Time Window	-4 +4	-4 +4	-4 +6	-4 +6
Observations	1,702	1,702	2,103	1,656
R-squared	0.760	0.922	0.680	0.358

a Bold type indicates that the coefficient estimate differs significantly from zero with 95% confidence

[b] Standard Error in parentheses, clustered by stock market and year

[c] Coefficients and Standard Errors multiplied by 100

Appendix C: Mechanisms

Cost of Waiting

TABLE C1 Difference-in-differences coefficients estimation. Treatment group divided into firms performing lower or higher than the industry median.

	Short-Term Effects		Long-Term Effects	
	(4.1)	(4.2)	(4.3)	(4.4)
	Scientific Intensity	Tech. Diversification	Avg. Quality	% Breakthroughs
Treated Low-Performing Firms * Post Treatment	**- .036**	**- .334**	**- .246**	- .035
	(.010)	**(.093)**	**(.090)**	(.020)
Treated High-Performing Firms * Post Treatment	- .007	**- .150**	**- .177**	**- .036**
	(.005)	**(.060)**	**(.084)**	**(.016)**
Time Window	-4 +4	-4 +4	-4 +6	-4 +6
Controls	Yes	Yes	Yes	Yes
Observations	1,944	1,944	2,401	1,872
R-squared	0.774	0.919	0.663	0.305

[a] Bold type indicates that the coefficient estimate differs significantly from zero with 95% confidence

[b] Standard Error in parentheses, clustered by stock market and year

Note: Low-Performing Firms are those treated firms with a five-years window average ROA lower than industry median in pre-treatment periods. High-Performing Firms are those treated firms with a five-years window average ROA higher than industry median post-treatment periods.

Predictability

TABLE C2 Difference-in-differences coefficients estimation. Treatment group divided into firms in stable or volatile industries.

	Short-Term Effects		Long-Term Effects	
	(5.1)	(5.2)	(5.3)	(5.4)
	Scientific Intensity	Tech. Diversification	Avg. Quality	% Breakthroughs
Treated Firms in Stable Industries * Post Treat.	**- .015**	**- .231**	**- .211**	**- .038**
	(.005)	**(.061)**	**(.080)**	**(.016)**
Treated Firms in Volatile Industries * Post Treat.	**- .013**	**- .137**	**- .188**	**- .032**
	(.005)	**(.067)**	**(.094)**	**(.016)**
Time Window	-4 +4	-4 +4	-4 +6	-4 +6
Controls	Yes	Yes	Yes	Yes
Observations	2,029	2,029	2,508	1,954
R-squared	0.772	0.920	0.677	0.351

[a] Bold type indicates that the coefficient estimate differs significantly from zero with 95% confidence

[b] Standard Error in parentheses, clustered by stock market and year

Note: Volatility of each firm *i* performance in a given year *t* (Risk $_{i,t}$) is the variance of the ROA_i in the five previous years (Bowman, 1980). To construct the average volatility of an industry *I* in a given year *t* (Risk $_{I,t}$), I computed the average overall Risk $_{i,t}$ by industry (three-digit NAICS) and compared it with the median volatility of all industries in a given year as a benchmark ($Risk_t$).. Stable industries are industries with a five-years window ROA standard deviation lower than median in pre-treatment periods. Volatile industries are industries with a five-years window ROA standard deviation higher than median in pre-treatment periods.

Related and Unrelated Diversification

TABLE C3 Difference-in-differences coefficients estimation for related and unrelated technological diversification

	(6.1) Related Diversification	(6.2) Unrelated Diversification
Treated * Post Treatment	**- .189**	- .018
	(.046)	(.027)
Time Window	-4 +4	-4 +4
Controls	Yes	Yes
Observations	2,035	2,035
R-squared	0.914	0.895

a Bold type indicates that the coefficient estimate differs significantly from zero with 95% confidence

b Standard Error in parentheses, clustered by stock market and year

Non-Granted Patent Applications

TABLE C4 Difference-in-differences coefficients estimation for granted and non-granted patent applications

	(7.1)	(7.2)	(7.3)	(7.4)	(7.5)
	Granted Applications	Non-Granted Applications	Granted w/ control for Total App.	Non-Granted w/ control for Total App.	Proportion Non-Granted Applications
Treated * Post Treatment	- .003	**- .009**	**.002**	**- .003**	**- .163**
	(.002)	**(.002)**	**(.001)**	**(.001)**	**(.054)**
Time Window	-4 +4	-4 +4	-4 +4	-4 +4	-4 +4
Controls	Yes	Yes	Yes	Yes	Yes
Observations	2,035	2,035	2,035	2,035	1,706
R-squared	0.947	0.956	0.989	0.987	0.421

[a] Bold type indicates that the coefficient estimate differs significantly from zero with 95% confidence

[b] Standard Error in parentheses, clustered by stock market and year

Note: Dependent variables are computed as *Ln(1+patent applications (Class-Year Adjusted))*. Models 7.1 and 7.2 compare the effect of the treatment with respect to granted and non-granted patents. Models 7.3 and 7.4 measures the effects controlling for the total patent applications, as *Ln(1+Total applications (Class-Year adjusted))*. Model 7.5 measures the effect as the ration of non-granted patent: *Ln(1+Non-Granted applications (Class-Year adjusted))/ Ln(1+Total applications (Class-Year adjusted))*.

Governance Matters

TABLE C5 Difference-in-differences coefficients estimation. Treatment group divided into firms with ownership concentration lower or higher than industry median.

	Short-Term Effects		Long-Term Effects	
	(8.1)	(8.2)	(8.3)	(8.4)
	Scientific Intensity	Tech. Diversification	Avg. Quality	% Breakthroughs
Treated Firms w/ Low-Ownership Concentration * Post Treat.	**- .011**	**- .279**	**- .213**	**- .035**
	(.005)	**(.059)**	**(.080)**	**(.016)**
Treated Firms w/ High-Ownership Concentration * Post Treat.	**- .030**	.110	- .130	**- .043**
	(.008)	(.072)	(.1)	**(.019)**
Time Window	-4 +4	-4 +4	-4 +6	-4 +6
Controls	Yes	Yes	Yes	Yes
Observations	1,983	1,983	2,445	1,907
R-squared	0.774	0.920	0.668	0.316

[a] Bold type indicates that the coefficient estimate differs significantly from zero with 95% confidence
[b] Standard Error in parentheses, clustered by stock market and year

Note: Firms with Low-ownership concentration are firms with 5-year window avg. HH index lower than industries than industry median in pre-treatment periods. Firms with High-ownership concentration are firms with 5-year window avg. HH index higher than industries than industry median in pre-treatment periods.

Managing Costs

TABLE C6 Difference-in-differences regression coefficients on research and design expenditures.

	(1)	(2)
Treated * Post Treatment	.138	.174
	(.114)	(.118)
Core-Technology Capabilities	.034	**.038**
	(.021)	**(.015)**
Size	**.789**	**.732**
	(.100)	**(.084)**
Return on Assets	**- .514**	**- .597**
	(.219)	(.200)
Institutional Ownership	.417	.336
	(.250)	(.211)
Debt-to-Equity [c]	- .007	- .008
	(.008)	(.008)
Tangibility	.562	.358
	(.463)	(.406)
Payout Ratio [d]	.012	.007
	(.009)	(.008)
Time Window	-4 +4	-4 +6
Observations	2,035	2,514
R-squared	0.953	0.953

a Bold type indicates that the coefficient estimate differs significantly from zero with 95% confidence

[b] Standard Error in parentheses, clustered by stock market and year

FIGURE C1 Difference-in-differences coefficients estimation of non-granted patents by year

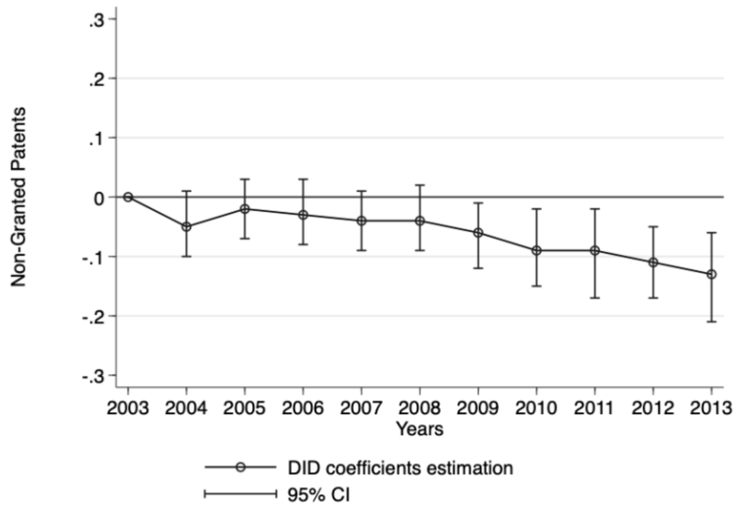
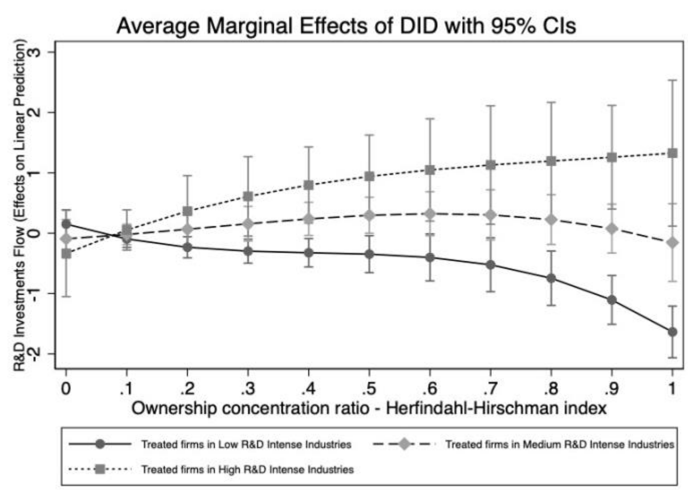


FIGURE C2 Marginal effect of difference-in-differences regression on research and design expenditures based on industry and ownership characteristics



Notes: 2003 is set as a baseline. Values are reported in terms of percentage of the standard deviation of ln(1+adjusted non-granted patents) of treated firms within the time window. The model includes control for ln(1+adjusted total patents). A coefficient of -0.1 corresponds to a drop of 10% of a standard deviation.