Product Market Power and Technological Innovation

Alexander Barinov
University of California Riverside

Hyun 'Shana' Hong
University of California Riverside

Ji Woo 'Ian' Ryou
West Virginia University

Xiao-Jun Zhang
University of California Berkeley

February 2022[◊]

Abstract
Product market power serves as a natural hedge against adverse shocks and competitive threats, thus increasing managerial risk tolerance of innovation investment. Consistent with that, we find that product market power is positively associated with firm innovation input and output. Additionally, consistent with learning from the leader's market valuation, we find that firm innovation is positively and significantly sensitive to market valuation of its product market leader, especially if the stock price of the leader/followers is more/less informative. The follower firms alter their R&D investments based on stock return around their leader's patent grant dates. The followers mimic innovation investments of their product market leader and private information in leader's prices is associated with improvement in their future profits. We find that liquidity shocks to leader's stock price hamper the following firms' learning. We conclude that product market power promotes innovation and firms learn from product market leader's market valuation.

Keywords: Product market leader, learning, technological innovation, market valuation, accounting quality

[◊] Alexander Barinov can be reached by email at abarinov@ucr.edu, Hyun 'Shana' Hong can be contacted by email at hyunh@ucr.edu, Ji Woo 'Ian' Ryou can be reached at jiwoo.ryou@mail.wvu.edu, Xiao-Jun Zhang can be contacted by email at xzhang@haas.berkeley.edu.

"*When you compare the top-performing firms in any sector to their lesser competition, there's a gap in productivity growth that continues to widen.*

The secret of the success of the Amazons, Googles and Facebook s of the world...is how much they invest in their own technology." (Wall Street Journal, July 26, 2018)

1. Introduction

Innovation, which includes creation of new business methods, development of new technologies, and introduction of new products and services to consumers, is the most significant force of firms' long-term success and survival (Solow, 1957; Romer, 1990). Market participants and the popular press view product market power, i.e., the power to command the price, quality, and characteristics of the product in the marketplace (Shepherd 1970), as an increasingly significant factor in determining the success of firm innovation and future profits.[1] The idea that product market power is a critical determinant of firm innovation dates back to Schumpeter (1942), who states that large firms with strong market positions are powerful engines of innovation. In this study, we examine a hitherto unexplored topic on whether and how firms' product market power affects their innovation. We further investigate whether followers' managers improve their innovation by mimicking and learning from information in stock prices of a product market leader. Following the literature, we define the product market leader as a firm with the largest sales volume in an industry categorized based on the Fama and French (1997) 48-industry classification (Derfus et al. 2008, McElheran 2015).

Firms are not isolated islands, yet often compete via continuous innovation to increase their market share, improve revenues and profits, and survive in the product market. Product market power arguably cultivates technological innovation through increased risk tolerance since firms with greater

[1] The product market leader has been dominatingly investing in technological innovation (R&D, brands, human resources, technology, and so forth) in the last decade compared to its competitors. Refer to Wall Street Journal article by Christopher Mims, July 26, 2018 9:00 a.m. ET. (https://www.wsj.com/articles/why-do-the-biggest-companies-keep-getting-bigger-its-how-they-spend-on-tech-1532610001)

market power have stable cash flows and are protected from product market threats (Peress 2010). The product market leader can thus experiment with riskier investment projects and acquire other firms in the supply chain or innovation-intensive smaller competitors to accelerate the rate of innovation process (Phillips and Zhdanov 2012). Product market power can also allow the product market leader to secure prospective monopoly rents via research and development (R&D), patents (Aghion and Howitt 1990; Caballero and Jaffe 1993), and economies of scale (Schumpeter 1942).[2] Accordingly, the gap of intangible investments between the market leader and other firms has been dramatically increasing in the last decade (Govindarajan et al. 2019). We thus hypothesize that the product market leader also leads other firms in the industry in terms of innovation.

The innovation advantage associated with the product market power can in turn allow managers of other firms in the industry to learn from the valuation of an industry leader when deciding their innovation policy. The market valuation of the leader informs followers about breakthroughs in leading innovative technologies, about their own investment opportunities as well as macro-economic or industry-wide cycle and volatility, thus complementing other information managers have, for example, the firm's own stock price. Hayek (1945) suggests that market valuations are a vital source of information that can provide guidance on the firm’s investment. Security prices include information of informed traders who have no other venue for delivering it to managers except via trading (Grossman and Stiglitz 1980; Glosten and Milgrom 1985; Kyle 1985). Hence, security prices include information that managers may not possess, for example, the information that updates managers’ beliefs on efficiency of their firm’s investments in innovation.[3] The literature on feedback from stock

[2] Consistently, anecdotal evidence shows that product market power has been recognized as an increasingly significant driver of firm innovation success. Refer to Wall Street Journal article by Christopher Mims, July 26, 2018 9:00 a.m. ET. (https://www.wsj.com/articles/why-do-the-biggest-companies-keep-getting-bigger-its-how-they-spend-on-tech-1532610001)

[3] Dye and Sridhar (2002), for instance, suggest that information from capital markets can be more accurate than that from the firm itself.

prices to investment decisions has largely focused on how firms use information in own stock prices to decide on capital investment.[4] Our point of departure lies at examining whether and how product market power affects firms' learning from the price of the market leader and using this information to guide innovation.

It is ex ante uncertain whether product market power contributes to corporate innovation and whether such learning from market leader's valuation occurs. Due to organizational inertia and agency problems in large firms, the product market leader may not be an efficient innovator compared to smaller firms. In addition, followers might lack motivation to learn. While the growing body of literature has focused on the informational effect of stock prices on firm capital investment (Beatty, Liao and Yu 2013; Foucault and Fresard 2014), firms tend to overinvest in physical capital, but underinvest in innovations (Holmstrom, 1989; Rong 2017). The underinvestment is partially due to risk aversion of managers whose equity portfolio is relatively less diversified (Berk, Stanton and Zechner 2010). Holmstrom (1989) indicates that firm innovation is a long-term process including idiosyncratic and uncertain factors and is naturally exposed to high frequency of failures, while Chen, Cheng, Lo and Wang (2015) show that managerial decisions are often myopic and have a short planning horizon. Risk-averse firm managers may not be sufficiently motivated to learn from market valuation of the product market leader (or stock prices in general).

We use U.S. sample of 202,569 firm-year observations during the sample period between 1979 and 2016. We use R&D-to-assets ratio as a proxy for innovation input and two proxies for corporate innovation output — the number of patents and patent citations, which capture the quantity and quality of firm innovation outputs, respectively (Hirshleifer et al. 2013). We define product market

[4] See Chen et al. (2007), Foucault and Fresard (2012), Edmans et al. (2012), Zuo (2016), Jennings and Mazzeo (1991), Luo (2005), Kau, Linck and Rubin (2008), Edmans, Jayaraman and Schneemeier (2017), Jayaraman and Wu (2019).

leaders as firms with the largest sales in a Fama and French (1997) industry and reevaluate annually if the leader still holds the leading position and has the largest sales in the industry.

We find that product market power leads to superior innovation: product market leader has 4-5 times more patents and citations than an average follower. We further find that product market power has an incremental explanatory power of corporate innovation beyond other firm characteristics. Controlling for other firm characteristics, product market leaders have higher R&D-to-assets ratios than followers, as well as higher innovation quantity and quality, as captured by patents and patent citations, respectively. We further find that R&D expenses, patent numbers, and citations of followers depend positively on market valuation of the industry leader, that is, its Tobin's Q. This last finding suggests that managers of followers learn from product market leaders' Q and employ this information to improve their firms' innovation decisions[5,6].

Having established the positive sensitivity of firm's innovation to its product market leader's Q, we next establish economic channels through which firm innovation is positively related to product market leader's stock valuations. These economic channels help us to triangulate our empirical results by showing that the positive sensitivity is driven by managerial learning from the product market leader's valuations, rather than common information held by a firm manager and investors in the industry leader. We find the positive sensitivity of firm innovation to product market leader's prices is stronger for firms with stronger managerial demand for industry leader's private information, and for firms whose product market leader's stock price impounds higher-quality private information. In addition, and again as uniquely predicted by the learning from leaders hypothesis, the sensitivity of a

[5] As an alternative proxy for the leader's market valuation, we employ a simple, noble Tobin's Q that includes intangible capital, "total Q" proposed by Peters and Taylor (2017). Specifically, the total Q equals the firm's market value divided by the sum of its physical and intangible capital stocks. We document that firm investments in innovation are sensitive to its leader's total Q, indicating that the learning is robust to alternative proxies for leader's market valuation.
[6] The sensitivity of firm innovation to its leader's valuation is stronger than the sensitivity to other benchmark valuations, such as the industry average Q or the small-capitalization firms' Q.

firm's R&D investment to its own Tobin's Q increases when its demand shocks are less likely to be correlated with those of its leader. First, we employ non-synchronicity of leader's stock price as a measure of private information in stock prices. Non-synchronicity is 1-R^2 from the regression of firm returns on market returns and industry returns (see, e.g., Durnev et al., 2003). The idea is that the component of a firm's stock return that is not explained by market and industry returns conveys firm-specific information. We predict and find that innovation of a firm is more sensitive to the industry leader's valuation (1) when the leader's stock price has more private information, as captured by higher stock price non-synchronicity; and (2) when firm managers' demand for their leader's private information is higher due to lack of private information in the firm's own price, as represented by firms' lower stock price non-synchronicity.

Second, we look at trading activity of insiders and profitability of their trades. Prior studies show that insiders have access to firms' private information and their trading facilitates the incorporation of firm-specific information into stock prices (Piotroski and Roulstone 2004). We predict and find that R&D expenses, patent numbers, and patent citations of followers are more sensitive to product market leader's valuation when the leader's insider trading activity is higher and insider's trades are more profitable. Conversely, we also show that R&D expenses, patent numbers, and patent citations of followers are more sensitive to product market leader's Q when managers of followers are less informed and thus more in need of outside private information on technological innovation, as captured by lower insider trading activity and lower insider trades' profitability.

Third, learning from the product market leader's valuation is more pronounced in R&D-intensive industries and when industry-wide cash flow volatility is higher. The motivation of followers to learn is expected to be higher in both cases: in R&D-intensive industries, innovation is more crucial for firm's survival, and industry-wide cash flow volatility can increase firm's risk and uncertainty, inducing the followers' managers to learn from the leader's market valuation.

Fourth, followers' R&D expenses, number of patents, and number of patent citations are more sensitive to the leader's Tobin's Q when follower's own stock price is less informative, as captured by lower institutional ownership. Institutional investors are considered sophisticated information intermediaries and is expected to accelerate the incorporation of firm-specific information into stock prices (Piotroski and Roulstone 2004).

Finally, we find that followers learn more from the leader's Q when product similarity between the product market leader and its following firms is higher, indicating that product similarity induces a firm manager to learn from the leader's valuation.

To sharpen our identification strategy, we further examine whether non-leading firms' innovation investments are affected by stock market reactions to their leader's patent application grant. When the three-day or the five-day stock returns around the leader's patent grant date are abnormally positive (negative), its followers increase (decrease) their R&D. Our results suggest that when a manager observes a large positive return to the leader's stock upon the leader's announcement of a major technological innovation, the manager concludes that the innovation is value increasing and allocate a more significant portion of R&D resources and human capital to that innovation.[7] In contrast, if the shares of the leader drop upon announcement, the manager seems to judge that the project is value-decreasing, and thus cancels or revises his R&D plans.

To address a potential endogeneity concern of the leader's market valuation, we employ mutual fund-induced liquidity shocks to the leader's stock prices as a measurement of noise trading (Xiao 2020) and find that noise in stock prices hampers the followers' learning from the leader's

[7] For example, Samsung Electronics Co. announced the Galaxy fold on March 20, 2019, the innovative technology used in the foldable phones. This technology is developed from the flexible OLED displays—technology developed by Samsung, world leader in manufacturing smartphone displays ("Mobile phones and smartphones with OLED screens", 2019). A three-day market-adjusted stock return for Samsung Electronics Co. around the announcement date is 3.64 percent and it experienced a significant increase in stock prices in the following years. After the announcement of the Galaxy fold, a flurry of industry competitors, including Motorola, Huawei and Xiaomi Technology, followed the Samsung Electronics' suit and developed foldable smart phones.

market valuation. These findings indicate that the relation between the leader's market valuation and following firms' innovation is more likely to be driven by the learning rather than unobservable firm characteristics.

To corroborate our above results on learning, we consider whether innovation activity of industry leader influences followers' innovation activities by checking whether R&D-to-assets ratio/patents number/patents citations of followers are related to those of the leader. The literature shows that firms imitate product market peers in other aspects, including the introduction of anti-takeover provisions and accreditation standards (Davis and Greve 1997; Chua and Petty 1999) and tax strategies (Kubick et al. 2015). Building on this strand of the literature, we contend that firms are likely to mimic their market leader's innovation endeavor because firms' innovation critically drives their success and survival in the product market (Hall 2002). We find that indeed the link between R&D-to-assets ratio/patents number/patents citations of followers and the product market leader is positive and particularly strong when the leader's stock price is more informative and more learning is likely to occur.

Lastly, we present evidence consistent with learning from valuations of the product market leader being value-improving for followers: the positive link between the leader's Tobin's Q and future profitability and cash flows of followers is stronger when stock price of the leader impounds more firm-specific information, as measured by the 1-R^2 non-synchronicity measure.

In summary, the main findings of our study are: (1) a product market leader has higher R&D intensity as well as patents and patent citations than other firms; (2) firm innovation is positively sensitive to private information reflected in market valuation of its product market leader; (3) the positive sensitivity is greater for firms with stronger demand for information; and (4) learning from market valuation of the leader contributes to successful mimicking of its innovation strategy. Overall, these findings are consistent with the conjecture that product market power contributes to improvement of technological innovation, managers of follower firms learn from market valuation of the product market leader and use this information to guide their innovations.

2. Hypothesis development

2.1 Product market power

Since the original work of Joseph Schumpeter (Schumpeter and Nichol 1934, Schumpeter 1942), researchers have continually examined whether and why product market power improves the success of innovation. Shepherd (1970) defines product market power as a firm's ability to govern the price, value, and characteristics of the product in the market. Product market power can offer greater opportunities and better economic incentives to innovate, as the industry leader position provides a natural hedge against adverse shocks and results (Peress 2010), permitting the firm to experiment with riskier projects. The availability of internal sources of funding to industry leaders ("deep pockets") can also increase their risk tolerance since the costs of failed innovation are less likely to jeopardize the firm's competitiveness. External sources of finance may also be more costly (because, for instance, of informational frictions between firm managers and outside capital suppliers) and firm proprietary information can be potentially revealed to its competitors if it seeks external capital for its investments in innovation (e.g., Bhattacharya and Ritter 1985). Having achieved patent protection, the market leader can enjoy the monopoly rent by blocking potential entrants. Gilbert and Newbery (1982) show that in an auction model of R&D existing monopolists invest more in innovation compared to prospective entrants, as total industry profits decrease when more firms enter the market and compete. Market leaders are thus considered to have the greatest economic incentives to preemptively innovate (Gilbert and Newbery 1982, Athey and Schmutzler 2001).

Several studies show that the level of innovation is remarkably superior among firms with strong market positions (Scherer 1967; Nicholas 2003). Consistently, recent anecdotal evidence shows that firms with product market power are powerful engines of technological progress, the biggest firm in every industry reporting the largest part of revenue, product margins and profits through investments in innovation, which other firms struggle to mimic. [8,9] Govindarajan et al. (2019) show that the innovation gap between small firms and large firms has been dramatically increasing in the last three decades. This gap is visible in medians and thus is not solely caused by the phenomenal achievement of a handful of firms including Amazon, Apple, Facebook and Google. The primary driver of this gap is the level of investment in tangible and intangible assets (R&D, brands, technology, human resources, etc.). The gap of the latter investment has dramatically increased in the last three decades. A recent study by Grullon, Larkin and Michaely (2019) shows that approximately 75% of US industries have experienced an increase in concentration levels in the last decade and this increase appears to arise from innovation. Yet, average firm investment in R&D declines, indicating that innovation becomes even more concentrated at leading firms. Thus, we predict that the industry leader is a more efficient innovator.

Not all researchers agree that the product market leader is an efficient technological innovator. Agency conflicts arising from managerial entrenchment may render research and development (R&D) activities in big firms ineffective, and big firm managers may be unwilling/unable to innovate efficiently because of organizational inertia. Young firms are often recognized as the more effective

---

[8] "Theory shows that market power can stimulate technological progress because firms innovate on the expectation of receiving monopoly rents. Thus, Philipe Aghion and his coauthors build on F. M. Scherer's inverted-U relationship where competition has a positive effect on innovation up to an inflexion point after which its effect decreases.7 Where rivals are close—in 'neck-and-neck' industries—competition always increases innovation, but in "unleveled industries" characterized by technology gaps competition may reduce incentives to innovate if laggards expect a reduction in their post-entry rents. The authors, using innovation data on a panel of U.K. firms, confirm the coexistence of competition and Schumpeterian innovation effects." Our recent market structure is similar to the latter and even though the firms with strong market positions do not take all, it takes most of it. Refer to Wall Street Journal article by Christopher Mims, July 26, 2018 9:00 a.m. ET. (https://www.wsj.com/articles/why-do-the-biggest-companies-keep-getting-bigger-its-how-they-spend-on-tech-1532610001)

[9] "But new data suggests that the secret of the success of the Amazons, Googles and Facebook s of the world—not to mention the Walmart s, CVSes and UPSes before them—is how much they invest in their own technology." (Source: https://www.wsj.com/articles/why-do-the-biggest-companies-keep-getting-bigger-its-how-they-spend-on-tech-1532610001)

innovator among researchers and practitioners (Acs and Audretsch, 1993, Kleinknecht, 1989, Kleinknecht and Reijnen, 1991, Scheirer, 1991). Hence, the efficiency of the product market leader is an empirical question, as our first hypothesis states (in the alternative form):

H1: *Product market power is positively correlated with innovation.*

2.2 Learning from product market leader's stock prices

Financial market development has been long recognized as spurring firm technological innovation and economic growth (Schumpeter 1942). Although a well-developed capital market is known to promote firm innovation by supplying capital (Rajan and Zingales 1998; Hsu, Tian and Xu 2014), there has been sparse research on information effect of financial markets on innovation. Security prices impound not only managerial information, but also collective opinion of traders on firm fundamentals that managers may not have access to otherwise. Hayek (1945) states that market prices are a valuable source of information about a firm's fundamentals that can guide investment. Bond, Edmans, and Goldstein (2012) introduce a new perspective on price efficiency, that is, revelatory price efficiency (RPE), which indicates the extent to which stock prices reflect information related to business efficiency. RPE facilitates learning from stock prices and helps decision makers make better decisions on production, investment, and innovation.

If a product market leader is the most efficient innovator, a manager of a follower firm has an incentive to learn about the product market leader's innovation from stock prices. For example, if a manager observes a large positive market reaction upon product market leader's announcement of a major technological innovation, he will possibly conclude that the innovation is value-increasing.[10] He

[10] For example, after Steve Jobs took to a stage more than a decade ago to introduce a world-shattering innovation: the first Apple iPhone, the stock price of Apple spiked. Its competitors such as Huawei Technologies Co. and Xiaomi Corp. subsequently followed and mimicked the Apple's innovation. Their innovation dramatically altered the way people conversed, commuted via the Uber and ordered lunch. The mobile age was ushered in.

may then choose to allocate more R&D resources and human capital to similar innovation. In contrast, if the market reacted negatively to the leader's innovation, it is likely that the follower's manager cancels or revises his R&D plans. These managerial actions render firm innovation sensitive to product market leader's price changes.

This sensitivity is naturally stronger when there is more private information impounded into the price in the trading process. A firm manager who can infer from stock prices of the market leader private information on innovation can better mimic its leaders' innovation. He can better evaluate demand for and supply of prospective innovative projects and trends in his industry and thus can allocate R&D resources and employees to the right place and time, increasing firm innovation efficiency. Managers can also better estimate and project returns on prospective innovative projects. Thus, holding everything else constant, we expect a manager with better access to private information via stock prices can more successfully learn from the market leader's innovation.

Prior research provides empirical evidence that managers learn from private information, but mainly focuses on the RPE of firm's own stock prices.[11] The exception is Foucault and Fresard (2014) showing that focal firm manager learns from peers' stock prices with respect to its capital investment, especially when its own stock price is less informative.

[11] Chen et al. (2007) show that sensitivity of corporate investment to the firm's own stock price is strongly and positively related to the amount of private information in the price. Foucault and Frésard (2012) find that firms cross-listed in US experience an increase in stock price informativeness and learn from stock prices more than firms that do not cross-list. Loureiro and Taboada (2015) find that mandatory International Financial Reporting Standards (IFRS) adoption, which is an exogenous shock to information environment across countries, improves insiders' ability to learn from stock prices about efficiency of merger and acquisitions. Zuo (2016) shows that the sensitivity of forecast revisions to concurrent stock returns increases as private information in prices increases, which supports the view that investors' private information helps managers enhance their forecast accuracy. Using the staggered enforcement of insider trading laws across 27 countries as a shock to the source of information, Edmans, Jayaraman and Schneemeier (2017) show that enforcement increases managerial learning, as the stock price impound more of outsiders' private information rather than managers' private information. Jayaraman and Wu (2019) show that mandatory segment disclosure hampers managerial learning by dampening informed trading and reducing stock price informativeness.

Motivated by the fact that the product market power is a vital determinant of innovation (Schumpeter and Nichol 1934, Schumpeter 1942) and innovation explains the increasingly dramatic gap in profits and operating performance between the market leader and others (Govindarajan et al. 2019), we predict that the market leader's stock prices provide valuable signal on its technological innovation to other firms. Hence, our second and third hypotheses (in an alternative form) are:

H2: *The sensitivity of a firm's innovation to the private information contained in its market leader's stock return is positive.*

H3: *The current-period inputs and the future innovation outputs of non-product market leading firms' innovation is positively correlated with the prior –period innovation of the product market leader firms.*

2. Variable Construction and Summary Statistics

2.1 Measures of Innovation

We use the ratio of R&D expenditures to total assets as a proxy for innovation input and two proxies for innovation output: the natural logarithm of one plus the number of patents (*LNPAT*) granted to each firm in each year and the natural logarithm of one plus the total number of citation count of patents granted during the year, adjusted by technology class (*LNCIT*). *LNPAT* captures quantity of innovation, while *LNCIT* measures innovation quality.

2.2 Data Sources and Summary Statistics

We extract financials and stock prices from Compustat North America and CRSP, respectively. Next, we obtain data on firm innovation from the patent database of Kogan, Papanikolaou, Seru, and Stoffman (2017), which covers all patents awarded by the U.S. Patent and Trademark Office

(USPTO)[12] and links each patent and its citations to a CRSP firm. Third, we collect institutional ownership data from Thomson-Reuters institutional holdings (13f) database. After merging these three sets of data files, our final sample constitutes 202,569 firm-year observations during the sample period 1979 and 2016.

Table 1 Panel A reports the sample distribution by year. The number of firms exhibits a relatively even and symmetric distribution over our sample period. Table 1 Panel B summarizes the sample distribution across 48 industries from Fama and French (1997). The most heavily represented industries are Business Services (10.05% of all firm-years), followed by banking (10.01%), Electronic Equipment (5.55%), and Retail (4.79%). In our multivariate regression analysis, we include year and industry fixed effects throughout all regression models so that the measures of corporate innovation are orthogonalized to industry-specific idiosyncratic characteristics.

[Insert Table 1 here]

Table 2 reports descriptive statistics of variables used in our primary regression analyses, separately for the product market leader and other firms in the industry (followers). All variables are winsorized at the top and bottom one percent of their distributions to mitigate undue influence of outliers. We provide detailed variable definitions in Appendix A.

The mean of *LNPAT* (*LNCIT*) are 2.4872 and 0.4652 (2.9209 and 0.6135) for the leader and followers, respectively, consistent with the product market leader having higher quantity and quality of innovation outputs. On the other hand, the mean of *RDEXP* are 0.0194 and 0.0342, for the leader and other firms, respectively, suggesting that, relative to their size, followers spend more on R&D than the product market leader.

[12] Our innovation output variables, number patents and patent citations, are from 1976–2010, the period that is covered by USPTO.

The univariate statistics for the control variables are largely consistent with those reported in prior studies (e.g., Chen et al. 2007 and He and Tian 2013). The mean of *ASSET* is 9.7141 and 5.4961 for the leader and other firms, respectively, and the mean of *Q is* 1.5815 and 1.8037 for the leader and its followers, respectively. The means indicate that the industry leader is a large established firm with lower growth opportunities than those of other firms in the industry. The mean of *CFO* is 0.1003 and 0.0429, respectively, indicating that the industry leader has deeper pockets than other firms in an industry (Peress 2010).

[Insert Table 2 here]

3. Innovation of Product Market Leader and Follower Firms

3.1. Product market power and technological innovation

In our analysis of the relationship between product market power and innovation, we use a multivariate regression model with industry and year fixed effects and with standard errors clustered at the firm-level. Our model is specified as follows:

$$\begin{aligned} RDEXP_{it} \text{ or } LNPAT_{it+3} \text{ or } LNCIT_{it+3} \\ &= \beta_0 + \beta_1 LEADER_{it} \\ &+ \sum \beta_n Leader\ Characteristics_{it} + \sum \beta_m Firm\ Characteristics_{it} \\ &+ \varepsilon_{it}, \qquad Eq. (1) \end{aligned}$$

where the dependent variable is either an innovation input variable (*RDEXP*) at year t or one of the two proxies for firm innovation (i.e., *LNPAT* and *LNCIT*) at year t+3. We follow He and Tian (2013) and choose the measure of firm innovation such as patent approvals and citations at year t+3 since it takes two or three year for patents to be approved. The independent variables include an indicator for product market leader (*LEADER)* that takes a value of one for firms whose sales are the largest in the Fama and French industry in a given year, and a set of the leader's and its following firms' characteristics. We also benchmark the leader's innovation against two different types of benchmark groups. The first benchmark is an industry average of innovation input (*INDMEAN_RDEXP t-1*) and outputs (*INDMEAN_LNPAT or INDMEAN_LNCIT t-1*) and the second is the innovation inputs (*BOTTOM_RDEXP t-1*) and outputs (*BOTTOM_LNPAT or BOTTOM_LNCIT t-1*) for firms in the lowest tercile of sales in the Fama and French industry classifier per year. We scale all independent variables with continuous values by their standard deviation. This scaling allows us to directly interpret the economic significance of the effects by observing the magnitude of the estimated coefficients.

Our main interest is in the sign and magnitude of β_1, which is predicted to be significantly positive, indicating that the product market leader is also an industry leader in innovations. We include a set of control variables to isolate the effect of product market power on innovation from other firm attributes that may affect firm innovation. Specifically, following Foucault and Fresard (2014), we control for economies of scale as well as organizational complexity of a given firm by including firm size (*SIZE*). We control for the level of firms' cash holdings (*CFO*) since the larger firm cash reserves may alleviate external capital frictions for its investments in innovation. When the dependent variable is R&D expenditure (*RDEXP*), we control for the stickiness of firm R&D expenditure by including past R&D expenditures (*RDEXP_LAG1* and *RDEXP_LAG2*).

Table 3 finds that β_1 is significantly positive (with p-value < 0.01) both when the dependent variable proxies for innovation input (*RDEXP*) and outputs (*LNPAT* and *LNCIT*), suggesting that product market leader invests in innovation more heavily and generates a higher quantity and quality of innovation compared to other firms of similar size and profitability. These findings are consistent with our primary hypotheses; that is, the product market power is positively correlated with innovation.

[Insert Table 3 here]

3.2. The Market valuation of Product market leader and Followers' Innovation

Motivated by the RPE viewpoint stating that managers learn from market prices and incorporate this information into their investment strategies (Chen et al. 2007; Loureiro and Taboada 2015; Zuo 2016) and the theory showing that product market leader position provides the competitive advantage to innovate (Schumpeter 1942), we empirically test our first two hypotheses. H2 indicates that when the product market leader has news on innovation, its Tobin's Q reflects that and other firms can learn from it. Thus, we predict a positive sensitivity of follower's innovation to industry leader's Tobin's Q. We test this prediction by estimating the following multivariate regression model:

$$\begin{aligned} RDEXP_{it} \; or \; LNPAT_{it+3} \; or \; LNCIT_{it+3} \\ &= \beta_0 + \beta_1 LEADER\_Q_{it} + \beta_2 FIRM\_Q_{it} \\ &+ \textstyle\sum \beta_n Leader\ Characteristics_{it} \; + \textstyle\sum \beta_m Firm\ Characteristics_{it} \\ &+ \varepsilon_{it}, \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad Eq.(2) \end{aligned}$$

where the dependent variable is either the innovation input variable (*RDEXP*) at year t or one of the two proxies for firm innovation (i.e., *LNPAT* and *LNCIT*) at year t+3. The independent variables include product market leader's Tobin's Q (*LEADER_Q)* and its following firms' Tobin's Q (*FIRM_Q)*, a set of product market leader's and follower's characteristics.

Our main interest is in the sign and magnitude of β_1, which is predicted to be significantly positive, indicating that a firm learns from product market leader's market valuation and alters its innovation strategy. We include a set of control variables to isolate the effect of leader's Q from other firm attributes that may affect firm innovation. We include the set of control variables for the leader and the non-leading firms, separately (Foucault and Fresard 2014).

Table 4 reports the regression results. We find that β_1 is significantly positive (with p-value < 0.05) both when the dependent variable proxies for innovation input (*RDEXP*) and outputs (*LNPAT* and *LNCIT*), suggesting that product market leader's market valuation is positively related to innovation for a given firm. These findings are consistent with our primary hypotheses; that is, the stock price of product market leader contains unique information, and managers learn from the valuation of product market leader and use this information to improve their firm's innovation.

[Insert Table 4 here]

4. When Do Followers Learn More from Product Market Leader's Valuations?

H2 states that the sensitivity of followers' innovation to the leader's Tobin's Q will be greater if the stock price of the leader contains more private information, which is unavailable to its followers other than from observing the stock price dynamics. Conversely, this sensitivity will be less when a firm manager has an opportunity to learn private information in its own stock price. We test these predictions by employing two types of private information, that is, private information (1) of the product market leader and (2) its following firms and estimate our main multivariate regression model (Eq. (2)) in two subgroups, Low and High private information.

4.1 Private Information of Product market leader

Our first measure of private information is stock price non-synchronicity from Roll (1988), 1-R^2 from the regression of firm returns on the market return and industry return. Roll (1988) shows that this proxy is not related to public news, and thus, represents firm's private information. Subsequent work has provided supporting empirical evidence that firm-specific return variation is an effective proxy for private information in stock prices (Morck, Yeung, and Yu 2000; Durnev et al. 2003; and Durnev, Morck, and Yeung 2004). Thus, if 1-R^2 is high, we expect a more positive relation between followers' innovation and the leader's Q.

Our second measure of private information is trading activity of insiders and profitability of their trades. We predict that the firm manager is more likely to learn from its product market leader's market valuation when executives of the leader appear to have private information, as captured by their trades and abnormal returns they earn. Hence, the sensitivity of followers' innovation to the leader's Tobin's Q will be greater if the leader's executives trade more and do so more profitably.

To measure the impact of product market leader's private information, we employ the above proxies for the product market leader's private information per year, and categorize the sample into the three groups, based on the level of private information. We then run our main regression model of learning (Eq. (2)) in these subgroups separately and report the regression results for the extreme two terciles in Table 5.

Table 5, Panel A shows that the link between followers' innovation and the leader's Q (β_1 from Eq. 2) is more significant and positive when the leader is categorized into the highest tercile of stock price non-synchronicity (with p-value < 0.01). This result indicates that when the leader's stock price includes more firm-specific idiosyncratic information, its following firms are more likely to learn from the leader's valuations.

Panel B and C report the results when *PRIVATE_INFO* of the leader is proxied by the abnormal return and volume of leader's insider trading, respectively. We compute insider trading return as the annual average of the one-month buy-and-hold excess returns following insider trades. We measure the insider trading volume as the number of shares traded by insiders in a given year divided by the total number of shares traded. Following the literature (e.g., Foucault and Fresard 2014), we only use insider trading by open market stock transactions conducted by the top five corporate executives (CEO, CFO, COO, President, and Chairman of the Board).

Panel B and C show that β_1 is more significant and positive when the leader's insider trading return and volume belong to the highest tercile (with p-value < 0.10) except when the dependent variable is *LNPAT t+3*. [13] These results are supportive of the idea that when executives of the product market leader appear to be more informed, the follower firms are more likely to learn from the leader's valuation when followers decide on their own innovation.

Table 5 also controls for firm's own Q, since the leader and the followers are likely to enjoy a similar information environment, and if the leader's price has more private information about the leader, the followers' prices are also likely to have more private about the followers. We do observe that followers also learn from their own prices more when the leader's price is more informative, but our results hold even controlling for that.

To sum up, Table 5 supports our second hypothesis; that is, the stock price of product market leader contains unique information, and followers use this information to improve their innovation.

[Insert Table 5 here]

4.2. Private Information of Follower Firms

Table 6 reports our main regression results of Eq. (2), conditional on the private information of non-leading firms. Panel A report the results of Eq. (2) with firm-year observations categorized into terciles, based on the follower's stock price non-synchronicity. Panel A shows that the sensitivity of follower's innovations to the leader's Q (β_1) is more significant and more positive (with p-value < 0.01) when the follower is categorized into the lowest tercile of its stock price non-synchronicity and firm stock price is less likely to contain firm-specific information. These results are consistent with the idea that when a firm manager has less opportunity to learn from the firm's own market valuations, he is more likely to rely on its leader's stock price dynamics.

[13] We have an unbalanced sample between the lowest and the highest tercile of abnormal insider trading return and volume in Panel B and C, respectively, since we replace the missing values of insider trading with zero. As a result, the sample distribution is highly skewed toward the lowest tercile that constitutes firms without insider trading.

Panel B and C report similar results with *PRIVATE_INFO* proxied by the follower's insider trading abnormal return and volume, respectively. When the follower's insider trading return and volume belongs to the lowest tercile, the sensitivity of firm innovation to its leader's valuation is stronger (with p-value < 0.10) except when the dependent variable is *LNCIT t+3*.

[Insert Table 6 here]

4.3 Influence of information environment

Institutional investors trade on value-relevant information they have and thus help stock prices become more informative (Chen et al. 2007, Bushee and Goodman 2007). If institutional ownership of the follower firm is low, its price will be less informative, and the manager will have to rely more on learning from the market valuation of the leader.

Panel A of Table 7 splits the sample into three terciles based on the followers' institutional ownership and estimates Eq. 2 separately for the lowest and highest tercile. We find significantly more positive coefficients on *LEADER_Q* (with p-value < 0.10) in the lowest tercile of institutional ownership except when the dependent variable is *LNCIT t+3*. Table 7, Panel A suggests that low institutional ownership and consequent dearth of information in followers' own stock price drive managerial demand for information in leader's market valuation to guide followers' innovation.

In the first two columns of Panel A that use the R&D-to-assets ratio as the dependent variable, we also observe that followers' learn more from their own price if institutional ownership of their shares is high. These columns present a clear picture that followers' managers learn from their firm's stock price if they can, and if this price is not as informative, they pay more attention to the leader's stock price.

4.4 Influence of product market threat

In this subsection, we investigate whether product market threat from rivals induces managers to learn more actively from the leader's market valuations. Hoberg et al. (2014) develop a firm-level competitive threat measure and show that product market threat alters firm's dividend and cash holding policies. Hoberg et al. (2014) use computational linguistics to analyze more than 42,000 firm transaction texts from firm annual reports and focus on product fluidity, an estimate of competitive threats faced by a firm in its product market that represent fluctuations in rival firms' products compared to the firm's product.

We employ these new text-based proxies from Hoberg et al. (2014) and expect a firm manager to look at market valuation of the product market leader more when the firm faces greater product market threat from rivals.

Table 7, Panel B reports regression results on managerial learning from the leader's market valuation (Eq. (2)), conditional on the level of product market threat. We find significant and positive coefficients on *LEADER_Q* (with p-value < 0.01) in the top product market threat tercile, but not in the bottom tercile. The difference between top and bottom tercile is statistically significant (p-value < 0.05) except for when we look at number of patents as the left-hand side variable.[14] Even more, we find that if product market threat is low, followers choose not to learn from the product market leader's stock prices at all.

Panel B also controls for learning from own stock price – it is possible that high product market threat causes managers to use their own firm's stock price as a guide for their innovation, and since followers' and the leader's stock prices are likely to be positively correlated, this effect can be picked up by the slope on the leader's Q if we do not control for the change in the slope on the firm's own Q (β_2 in Eq. 2). We do find in Panel B that the slope on the firm's own Q roughly doubles when product market threat is high, meaning that managers learn more from their own firm's stock prices

[14] The skewed distribution between the lowest and the highest terciles in Table 7, Panel C is caused by the product market threat variable designed by Hoberg et al. (2014) being measured per industry and year.

when they decide on innovations, but even controlling for that managers also learn more from the leader's Q if product market threat is high.

We conclude from Panel B that product market threat from rivals increases managerial demand for the information from the market leader's valuations.

4.5 Influence of industry R&D intensity

A firm manager is expected to have a stronger economic incentive to learn from product market leader's stock price when the firm operates in an R&D intensive industry. Such industry requires high level of R&D investment and managerial learning incentive with respect to product market leader's technologies is greater. To test this prediction, we categorize the sample into three subgroups based on the industry average R&D-to-assets ratio. As in the rest of the paper, our industries are 48 industries from Fama and French (1997).

Table 7, Panel C reports regression results on managerial learning from the leader's market valuation (Eq. (2)), conditional on the level of industry average of R&D intensity. We find significant and positive coefficients on *LEADER_Q* (with p-value < 0.05) in the top terciles of R&D intensity. The difference between top and bottom terciles is statistically significant (p-value < 0.05) except when the dependent variable is *LNCIT t+3*. Even more, in low R&D intensity industries, followers do not seem to pay attention to the leader's Q at all while deciding on their relatively less important innovation strategy. A similar pattern is visible in the loadings on the firm's own Q, but since both Qs are used in the same regression, those two patterns are two similar, but independent patterns, and none is picking up the other.

The results in Table 7, Panel C are consistent with followers' managers learning more from the leader's market valuations when their demand for information to guide their innovations is greater.

4.6 Influence of firm-level uncertainty

If accounting numbers are not reliable because of too much volatility in the firm fundamentals, managers are likely to seek additional information in stock prices. In particular, if the firm operates in an industry with volatile cash flows, we expect followers to learn more from the leader's market valuations. Industry cash flow volatility was used as a measure of firm-level uncertainty in previous studies (Frankel and Litov 2009; Opler et al. 1999; Yasai-Ardekani 1986); an advantage of using the industry cash flow volatility is that the firm cannot control this volatility by changing its accounting practices or sales strategy.

Panel D of Table 7 reports the results of estimating our main regression (Eq. 2) in three subgroups based on industry cash flow volatility. We find significant and positive coefficients on *LEADER_Q* (with p-value < 0.10) in the top cash flow volatility tercile. The difference between top and bottom terciles is statistically significant (with p-value < 0.05). These findings suggest that when faced with greater uncertainty, managers are more willing to learn from the product market leaders' valuation and change their innovations accordingly.

[Insert Table 7 here]

5. Additional Tests

5.1 Peers' R&D Investments, Conditioning on the Stock Return around Industry Leader's Patent Grant Date

Leader's Q gives us a broad look at the leader's innovation efficiency, but we acknowledge that Tobin's Q can be driven by many factors beyond innovation. To sharpen our identification strategy on the learning effect, we look at a particular event and its implications for the leader's stock price: patent being granted by USPTO.

If a firm manager is learning from the industry leader's market valuation, his innovation is likely to be affected by the leader's stock return around the patent grant date. The more favorable the market reaction to the leader's patent grants is, the more likely are the followers to strive to adopt a similar innovation and for that reason modify their own investments in innovation by reallocating human personnel and other corporate resources.

To test this prediction, we examine whether followers do invest more in R&D in the next three years if the leader's stock return around the patent grant date is favorable. We compute the leader's market-adjusted return in three or five days around the patent grant date (*LEADER_RET3* or *LEADER_RET5*), respectively, and then run the following multivariate regression model:

$$INDUSTRY\ PEER\ RDEXP_{it,t+3} = \beta_0 + \beta_1 * (LEADER_{RET3}\ or\ LEADER_{RET5_{it}}) + \sum \beta_n \text{CONTROLS} + \varepsilon \qquad \text{Eq. (3)}$$

Our main interest is the sign of β_1, which represents the sensitivity of industry peers' R&D to their leader's return around the grant date. The results of estimating Eq. (3) are reported in Table 8, which shows that β_1 is positive and significant (with p-value < 0.05) and suggests that industry peers are more likely to increase their R&D investments when the stock market reaction to their leaders' patent grant is favorable. While patent grant is a single event and there are multiple other events and ways of information innovation getting into the leader's stock price, the test with announcement returns at the patent grant dates is a particularly clean example of followers learning from the leader's stock price and using this information to guide their decisions on innovation.

[Insert Table 8 here]

5.2 Mimicking of Product Market Leader's Innovation

In this subsection, we examine the extent to which firms mimic the R&D investments of product market leaders by modifying Eq. (2) to include the leader's innovation variables instead of the leader's Q:

$$\begin{aligned}
&RDEXP_{it} \ or \ LNPAT_{it+3} \ or \ LNCIT_{it+3} \\
&= \beta_0 \\
&+ \beta_1 LEADER_RDEXP_{it-1} \ or \ LEADER_LNPAT_{it-1} \ or \ LEADER_LNCIT_{it-1} \\
&+ \beta_2 LEADER_SPI_{it-1} \\
&+ \beta_3 (LEADER_RDEXP_{it-1} \ or \ LEADER_LNPAT_{it-1} \ or \ LEADER_LNCIT_{it-1}) \\
&\times LEADER_SPI_{it-1} \\
&+ \ \textstyle\sum \beta_n Leader \ Characteristics_{it-1} \ + \ \sum \beta_m Firm \ Characteristics_{it-1} \\
&+ \varepsilon_{it}, \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad Eq.(4)
\end{aligned}$$

where the leader's innovation is measured in year t-1, while the following firms' *RDEXP, LNPAT* and *LNCIT* are measured in year t, t+3 and t+3, respectively, and $LEADER_SPI_{it-1}$stands for the 1-R^2 stock price non-synchronicity measure of the industry leader, one of our proxies for the amount of private information in the stock price.

Table 9 presents results of estimating Eq. 4 and shows that firms mimic innovation investments of product market leaders, as we find positive and significant coefficients, β_1, on $LEADER\_RDEXP_{it-1} \ or \ LEADER\_LNPAT_{it-1} \ or \ LEADER\_LNCIT_{it-1}$ (with p < 0.05). What is even more important, the positive coefficients are stronger or largely driven by the interaction between *LEADER_SPI* and $LEADER\_RDEXP_{it-1} \ or \ LEADER\_LNPAT_{it-1} \ or \ LEADER\_LNCIT_{it-1}$, indicating that it is the private information impounded to leader's stock price dynamics drives non-leading firms' mimicking behavior.

Overall, our results suggest that firms' R&D investments and innovation outputs are associated with the R&D investments and innovation outputs of their product market leader in the preceding period, supportive of the view that followers imitate innovation strategy of their leaders using the information followers obtain from the leader stock price.

[Insert Table 9 here]

5.3 Future operating performance

Our analysis up to this point shows that followers learn from the industry leader's Q and use this information to change their innovation strategy. The question that remains is whether this learning improves the performance of the firm by, for example, making it more profitable.

We measure future performance as operating profitability (*Profitability*) or operating cash flow (*CFO*) at year *t +3*. *Profitability* is defined as earnings before interest, tax, depreciation, and amortization divided by the total assets and *CFO* equals net cash flow from operation divided by the total assets. We then regress *Profitability* and *CFO* for *t+3* on our main variables (*LEADER_Q* and *LEADER_SPI*) along with their interaction and a set of two controls. Specifically, we run the following multivariate regression model:

$$\begin{aligned} Profitability_{it+3}\ or\ CFO_{it+3} &= \beta_0 + \beta_1 LEADER_{Q_{it}} + \beta_2 LEADER\_SPI_{it} \\ &+ \beta_3 LEADER\_Q_{it} \times LEADER\_SPI_{it} \\ &+ \textstyle\sum \beta_n Leader\ Characteristics_{it} \\ &+ \textstyle\sum \beta_m Firm\ Characteristics_{it} \\ &+ \varepsilon_{it}, \qquad\qquad Eq. (5) \end{aligned}$$

The main coefficient of interest is β_3: we do not have a prior whether the leader's Q is going to be negatively correlated with the follower's profitability (competition) or positively correlated (all firms in the industry face similar shocks), but our prior result that higher leader's Q makes followers innovate more (i.e., start more positive NPV projects) and that this link is stronger if the leader's price is more informative (*LEADER_SPI,* in this case the 1-R^2 price non-synchronicity measure, is higher) suggests that the relation between the leader's Q and follower's profitability becomes more positive if more value-enhancing learning from the leader's Q (and more useful innovation) is taking place. Table 10 presents the results of estimating Eq. 5. We find significantly positive coefficients on *LEADER_Q* × *LEADER_SPI* (with p-value < 0.01), which imply that the learning leads to superior future operating performance and supports the view that information incorporated into the leader's private information helps managers improve their innovation strategy.

[Insert Table 10 here]

5.4 Mutual Fund Flow Volatility Pressure

Our preceding analysis shows that learning from the leader's Q happens more when the leader's stock price is more informative. While we control for the firm's own Q and information in the firm's own stock price, it is still possible that informativeness of the leader's and followers' stock price are correlated, and firms are learning from their own price and not the leader's price. Also, measures of stock informativeness can be imperfect and be correlated with other variables like size, liquidity, etc.

To address this potential endogeneity concern, we exploit a liquidity and volatility-induced shock to the leader's and the firm's stock prices. Specifically, we go the opposite way and look at the part of stock prices that is definitely not information driven– the price pressure created by mutual fund forced sales. We exploit mutual fund flow volatility from Xiao (2020) as a measure of noise trading, and test whether noise in stock prices hampers followers' learning.

We collect domestic equity funds' size and return data from the CRSP Survivor-Bias-Free Mutual Fund Database and mutual fund stock holding data from Thomson Reuters. Following the prior literature, we exclude sector funds, not to have the proxy contaminated by industry fundamentals

(Edmans, Goldstein, and Jiang 2012; Xiao 2020).[15] Using data on mutual funds' size and return, we compute monthly fund flow as follows:

$$F_{k,m} = \frac{TNA_{k,m} - TNA_{k,m-1}(1 + R_{k,m})}{TNA_{k,m-1}} \qquad Eq. (6)$$

where $TNA_{k,m}$ denotes total net assets of fund k at the end of month m, and $R_{k,m}$ denotes the reported return of fund k over month m. We winsorize monthly fund flows greater than 1,000% or less than -90% to circumvent the undue influence of extreme outliers (Ben-David et al. 2019). We then follow Xiao (2020) and measure. We calculate the aggregate fund flow volatility measure per firm and year, as follows:

$$MFFlowVol_{i,t} = \left(\frac{1}{\theta_{i,t-1}^{2}} W_{i,t-1}' \Omega_t W_{i,t-1}\right)^{\frac{1}{2}}, \qquad Eq. (7)$$

where $\boldsymbol{\Omega}_t$ is a K × K variance-covariance matrix of monthly fund flows across mutual funds over year t, $\theta_{i,t-1}$ denotes the market capitalization of stock i at the beginning of year t, and $W_{i,t-1}' = (w_{i,1,t-1}, \ldots, w_{i,k,t-1})$ denotes a 1 × K vector of dollar ownership of each mutual fund k in stock i at the beginning of year t. *MFFlowVol* estimates the hypothetical pressure of mutual fund flow-induced trading on stock return volatility, considering both the concentration of ownership and the volatility and/or correlation of the fund flows.

We use *MFFlowVol* to identify mutual fund noise trading that may be detrimental to firms' real performance. The identifying assumption is that *MFFlowVol* is driven by exogenous funding liquidity shocks to mutual funds and thus is not related to firms' fundamentals. We then regress our innovation input and output variables onto the leader's and firm's *MFFlowVol*, a set of product market leader's characteristics and a set of its following firms' characteristics as follows:

[15] We combine the two data files using MFLINKS files from WRDS.

$$
\begin{aligned}
RDEXP_{it} \ or \ LNPAT_{it+3} \ or \ LNCIT_{it+3} \\
&= \beta_0 + \beta_1 LEADER\_MFFlowVol_{it} + \beta_2 FIRM\_MFFlowVol_{\ it} \\
&+ \textstyle\sum \beta_n Leader\ Characteristics_{it} + \textstyle\sum \beta_m Firm\ Characteristics_{it} \\
&+ \varepsilon_{it}, \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad Eq.(8)
\end{aligned}
$$

where the dependent variable is an innovation input variable (*RDEXP*) at year t and the two proxies for firm innovation (i.e., *LNPAT* and *LNCIT*) at year t+3.

Table 11 presents the results of these regressions. We find insignificant and negative coefficients on *LEADER_ MFFlowVol*, consistent with the leader's noisy stock price impeding firm's learning on the leader's innovation endeavor. In addition, we find that the coefficients on are significant and negative with p-value < 0.10 except when the dependent variable is $RDEXP_t$. A similar negative relation exists between the innovation measures and *FIRM_MFFlowVol* (now the insignificant variable is $LNCIT_{t+3}$). This finding corroborates our main results that firms learn from the product market leader's market valuation concerning its technological innovation.

[Insert Table 11 here]

7. Conclusions

The economics literature defines product market power as firms' capacity to dominate the price, quality, and the nature of a product in a market (Shepherd 1970). Product market power serves as a natural hedge against adverse shocks and isolates firms from predatory risk in the product market (Hou and Robinson 2006; Irvine and Pontiff 2009; Peress 2010). Thus, product market power naturally increases managerial risk tolerance and cultivates innovation, which is exposed to high frequencies of failure and uncertainty (Hall 2002). In this study, we show the positive impact of product market power on firm technological innovation. We further document a positive and significant sensitivity of firm innovation to product market leader's stock prices. We find that a firm manager demands product market leader's information to a more significant extent when uncertainty is higher, when the firm is facing a higher degree of product market threat and when the firm is located in R&D-intensive industries. We also find that the improved innovation related to its product market leader's price informativeness leads to a firm's future superior operating performance. These findings imply that followers' managers learn from the industry leader's stock price and use this information to improve their innovation strategy.

References

Acs, Z. and Audretsch, D., 1993. Small firms and entrepreneurship. Cambridge University Press.

Aghion, P. and Howitt, P., 1990. A model of growth through creative destruction (No. w3223). National Bureau of Economic Research.

Andrews, D. and De Serres, A., 2012. Intangible assets, resource allocation and growth.

Athey, S. and Schmutzler, A., 2001. Investment and market dominance. *RAND Journal of economics*, pp.1-26.

Barnett, W.P. and McKendrick, D.G., 2004. Why are some organizations more competitive than others? Evidence from a changing global market. *Administrative Science Quarterly*, 49(4), pp.535-571.

Beatty, A., Liao, S. and Yu, J.J., 2013. The spillover effect of fraudulent financial reporting on peer firms' investments. *Journal of Accounting and Economics*, 55(2-3), pp.183-205.

Berk, J.B., Stanton, R. and Zechner, J., 2010. Human capital, bankruptcy, and capital structure. The *Journal of Finance*, 65(3), pp.891-926.

Bhattacharya, S. and Ritter, J.R., 1985. Innovation and Communication: Signaling with.

Bond, P., Edmans, A. and Goldstein, I., 2012. The real effects of financial markets. *Annu. Rev. Financ. Econ.*, 4(1), pp.339-360.

Bushee, B.J. and Goodman, T.H., 2007. Which institutional investors trade based on private information about earnings and returns?. *Journal of Accounting Research*, 45(2), pp.289-321.

Caballero, R.J. and Jaffe, A.B., 1993. How high are the giants' shoulders: An empirical assessment of knowledge spillovers and creative destruction in a model of economic growth. *NBER macroeconomics annual*, *8*, pp.15-74.

Chen, X., Cheng, Q., Lo, A.K. and Wang, X., 2015. CEO contractual protection and managerial short-termism. *The Accounting Review*, 90(5), pp.1871-1906.

Chen Q, Goldstein, I., and Jiang, W. 2007. Price informativeness and investment sensitivity to stock price. *Review of Financial Studies* 20(3): 619-650.

Chua, W.F. and Petty, R., 1999. Mimicry, director interlocks, and the interorganizational diffusion of a quality strategy: A note. *Journal of Management Accounting Research*, *11*, p.93.

Davis, G.F. and Greve, H.R., 1997. Corporate elite networks and governance changes in the 1980s. *American journal of sociology*, *103*(1), pp.1-37.

Dechow, P., Sloan, R., Sweeney, A., 1995. Detecting earnings management. *The Accounting Review* 70,193–225.

Demerjian, P.R., Lev, B., Lewis, M.F. and McVay, S.E., 2012. Managerial ability and earnings quality. *The Accounting Review*, 88(2), pp.463-498.

Derfus, P.J., Maggitti, P.G., Grimm, C.M. and Smith, K.G., 2008. The Red Queen effect: Competitive actions and firm performance. *Academy of Management Journal*, *51*(1), pp.61-80.

Durnev, A., Morck, R., Yeung, B. and Zarowin, P., 2003. Does greater firm‐specific return variation mean more or less informed stock pricing?. *Journal of Accounting Research*, 41(5), pp.797-836.

Durnev, A., Morck, R. and Yeung, B., 2004. Value‐enhancing capital budgeting and firm‐specific stock return variation. *The Journal of Finance*, 59(1), pp.65-105.

Edmans, A., Goldstein, I., and Jiang, W. 2012. The real effects of financial markets: The impact of prices on takeovers. *The Journal of Finance* 67(3): 933-971.

Edmans, A., Jayaraman, S. and Schneemeier, J., 2017. The source of information in prices and investment-price sensitivity. *Journal of Financial Economics*, *126*(1), pp.74-96.

Fama E. F., and French, K. R. 1997. Industry costs of equity. *Journal of Financial Economics* 43(2): 153-193.

Foucault, T., and Frésard, L. 2012. Cross-listing, investment sensitivity to stock price, and the learning hypothesis. *Review of Financial Studies* 25(11): 3305-3350.

Frankel, R. and Litov, L., 2009. Earnings persistence. *Journal of Accounting and Economics*, *47*(1-2), pp.182-190.

Ge, W., Matsumoto, D. and Zhang, J.L., 2011. Do CFOs have style? An empirical investigation of the effect of individual CFOs on accounting practices. Contemporary Accounting Research, 28(4), pp.1141-1179.

Gilbert, R.J. and Newbery, D.M., 1982. Preemptive patenting and the persistence of monopoly. *The American Economic Review*, pp.514-526.

Glosten, L.R. and Milgrom, P.R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of financial economics*, 14(1), pp.71-100.

Govindarajan, V., Lev, B., Srivastava, A. and Enache, L., 2019. The gap between large and small companies is growing. Why?. *Harvard Business Review*, 16.

Grossman, S.J. and Stiglitz, J.E., 1980. On the impossibility of informationally efficient markets. The *American economic review*, 70(3), pp.393-408.

Grullon, G., Larkin, Y. and Michaely, R., 2019. Are US industries becoming more concentrated?. *Review of Finance*, 23(4), pp.697-743.

Hall, B.H., 2002. The financing of research and development. *Oxford review of economic policy*, 18(1), pp.35-51.
He, J., Tian, X. 2013. The dark side of analyst coverage: the case of innovation. *Journal of Financial Economics* 109, 856-878.
Hirshleifer, D., Hsu, P.H. and Li, D., 2013. Innovative efficiency and stock returns. *Journal of financial economics*, 107(3), pp.632-654.
Hoberg, G., Phillips, G. and Prabhala, N., 2014. Product market threats, payouts, and financial flexibility. *The Journal of Finance*, 69(1), pp.293-324.
Holmstrom, B., 1989. Agency costs and innovation. *Journal of Economic Behavior & Organization*, *12*(3), pp.305-327.
Hou, K. and Robinson, D.T., 2006. Industry concentration and average stock returns. *The Journal of Finance*, 61(4), pp.1927-1956.
Hsu, P.H., Tian, X. and Xu, Y., 2014. Financial development and innovation: Cross-country evidence. Journal of Financial Economics, 112(1), pp.116-135.
Hayek, F.A., 1945. The use of knowledge in society. The *American economic review*, 35(4), pp.519-530.
Irvine, P.J. and Pontiff, J., 2009. Idiosyncratic return volatility, cash flows, and product market competition. *The Review of Financial Studies*, 22(3), pp.1149-1177.
Jayaraman, S. and Wu, J.S., 2019. Is silence golden? Real effects of mandatory disclosure. *The Review of Financial Studies*, 32(6), pp.2225-2259.
Jennings, R.H. and Mazzeo, M.A., 1991. Stock price movements around acquisition announcements and management's response. *Journal of Business*, pp.139-163.
Jones, J. 1991. Earnings management during import relief investigations. *Journal of Accounting Research* 29: 193-228.
Kau, J.B., Linck, J.S. and Rubin, P.H., 2008. Do managers listen to the market?. *Journal of Corporate Finance*, *14*(4), pp.347-362.
Kleinknecht, A., 1989. Firm size and innovation. *Small Business Economics*, 1(3), pp.215-222.
Kleinknecht, A. and Reijnen, J.O., 1991. More evidence on the undercounting of small firm R&D. *Research policy*, 20(6), pp.579-587.
Kogan, L., Papanikolaou, D., Seru, A. and Stoffman, N., 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, *132*(2), pp.665-712.
Kubick, T.R., Lynch, D.P., Mayberry, M.A. and Omer, T.C., 2014. Product market power and tax avoidance: Market leaders, mimicking strategies, and stock returns. *The Accounting Review*, *90*(2), pp.675-702.
Kyle, A.S., 1985. Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, pp.1315-1335.
Loureiro G, and Taboada, A. G. 2015. Do improvements in the information environment enhance insiders' ability to learn from outsiders? *Journal of Accounting Research* 53(4): 863-905.
Luo, Y., 2005. Do insiders learn from outsiders? Evidence from mergers and acquisitions. *The Journal of Finance*, 60(4): 1951-1982.
McElheran, K., 2015. Do market leaders lead in business process innovation? The case (s) of e-business adoption. *Management science*, 61(6), pp.1197-1216.
Morck, R., Yeung, B. and Yu, W., 2000. The information content of stock markets: why do emerging markets have synchronous stock price movements?. *Journal of financial economics*, 58(1-2), pp.215-260.
Nicholas, T., 2003. Why Schumpeter was right: innovation, market power, and creative destruction in 1920s America. *The Journal of Economic History*, 63(4), pp.1023-1058.

Opler, T., Pinkowitz, L., Stulz, R. and Williamson, R. 1999. The determinants and implications of corporate cash holdings. *Journal of Financial Economics* 52(1): 3-46.

Peress, J., 2010. Product market competition, insider trading, and stock market efficiency. *The Journal of Finance*, *65*(1), pp.1-43.

Peters, R.H. and Taylor, L.A., 2017. Intangible capital and the investment-q relation. *Journal of Financial Economics*, 123(2), pp.251-272.

Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of financial studies*, 22(1), pp.435-480.

Phillips, G.M. and Zhdanov, A., 2013. R&D and the incentives from merger and acquisition activity. The Review of Financial Studies, 26(1), pp.34-78.

Piotroski, J.D. and Roulstone, D.T., 2004. The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. The accounting review, 79(4), pp.1119-1151.

Rajan, R.G. and Zingales, L., 1998. Power in a Theory of the Firm. The Quarterly Journal of Economics, 113(2), pp.387-432.

Romer, P.M., 1990. Endogenous technological change. *Journal of political Economy*, *98*(5, Part 2), pp.S71-S102.

Solow, R.M., 1957. Technical change and the aggregate production function. *The review of Economics and Statistics*, *39*(3), pp.312-320.

Scheirer, W.K., 1991. Firm size and innovation: a comment. *Small Business Economics*, 3(2), pp.155-156.

Scherer, F.M., 1967. Market structure and the employment of scientists and engineers. *The American Economic Review*, 57(3), pp.524-531.

Schneemeier, J., 2017. Shock propagation through cross-learning with costly price acquisition. Working Paper.

Schumpeter, J.A. and Nichol, A.J., 1934. Robinson's economics of imperfect competition. *Journal of political economy*, 42(2), pp.249-259.

Schumpeter, J., 1942. Creative destruction. *Capitalism, socialism and democracy*, *825*, pp.82-85.

Shepherd, W.G., 1970. Market power and economic welfare: an introduction.

Xiao, S.C., 2020. Do noisy stock prices impede real efficiency?. *Management Science*, 66(12), pp.5990-6014.

Yasai-Ardekani, M., 1986. Structural adaptations to environments. *Academy of Management Review* 11(1): 9-21.

Zhong, R.I., 2018. Transparency and firm innovation. *Journal of Accounting and Economics*, 66(1), pp.67-93.

Zuo, L., 2016. The informational feedback effect of stock prices on management forecasts. *Journal of Accounting and Economics*, *61*(2-3), pp.391-413.McElheran, K., 2015.

Appendix A

Variables Definition

LEADER_DUMMY = A dummy variable that takes the value of one for a firm that is the product market leader in one of the 48 Fama and French (1997) industries; otherwise the dummy variable equals zero. We define leaders as firms that have the largest market share in a given industry-year.

RDEXP = Research and development expenditure scaled by total assets at the end of fiscal year *t*.

LNPAT = The natural logarithm of one plus firm *i*'s total number of patents

LNCIT = The natural logarithm of one plus firm *i*'s total number of citations received on the firm's patents

LEADER_RDEXP = *RDEXP* of the product market leader.

LEADER_LNPAT = *LNPAT* of the product market leader.

LEADER_LNCIT = *LNCIT* of the product market leader.

INDMEAN_RDEXP = Industry average of *RDEXP* in a Fama and French (1997) industry classifier per year.

INDMEAN_LNPAT = Industry average of *LNPAT* in a Fama and French (1997) industry classifier per year.

INDMEAN_LNCIT = Industry average of *LNCIT* in a Fama and French (1997) industry classifier per year.

BOTTOM_RDEXP = Bottom tercile's average of *RDEXP* in a Fama and French (1997) industry classifier per year, based on market capitalization

BOTTOM_LNPAT = Bottom tercile's average of *LNPAT* in a Fama and French (1997) industry classifier per year, based on market capitalization

BOTTOM_LNCIT = Bottom tercile's average of *LNCIT* in a given industry-year, based on product market power (Market Share)

LEADER_Q = Market value of equity plus book value of assets minus book value of equity, scaled by book value of assets of the product market leader. We define firms which has the largest market share in a given industry-year as the product market leaders.

FIRM_Q = Market value of equity plus book value of assets minus book value of equity, scaled by book value of assets of the focal firm.

LEADER_ASSET = The natural log of total assets of the product market leader. We define firms which has the largest market share in a given industry-year as the product market leaders.

FIRM_ASSET = The natural log of total assets of the focal firm.

LEADER_CFO =Operating Cash Flow, scaled by total asset, of the product market leader. We define firms which has the largest market share in a given industry-year as the product market leaders.

FIRM_CFO =Operating Cash Flow, scaled by total asset, of the focal firm.

LEADER_LEV = Leverage Ratio, defined as debt divided by total assets at the end of fiscal year t, of the product market leader. We define firms which has the largest market share in a given industry-year as the product market leaders.

FIRM_LEV = Leverage Ratio, defined as debt divided by total assets at the end of fiscal year t, of the focal firm.

PROFITABILITY = Return on assets ratio defined as Income before extraordinary items divided by total assets at the end of fiscal year t.

INDUSTRYPEER_RDA = Firm's R&D expenditure scaled by total assets in the Fame-French industry classifier of the product market leader.

LEADER_RET3 = Three-day cumulative abnormal returns around product market leaders' patent grant date, adjusted by its cumulative stock returns between 210 and 11 days prior to the grant date.

LEADER_RET5 = Five-day cumulative abnormal returns around product market leaders' patent grant date, adjusted by its cumulative stock returns between 210 and 11 days prior to the grant date.

MFFLOWVOL= Volatility of mutual fund flow per firm and year as designed by Xiao (2020).

LEADER_MFFLOWVOL= Product market leader's *MFFLOWVOL*.

FIRM_MFFLOWVOL = Firm's *MFFLOWVOL*.

SPI = A measure of firm-specific information arriving to the security market based on R^2 from the augmented market model regression. Specifically, SPI = $\ln((1 - R^2)/R^2)$. The augmented market model regression follows as: $r_{i,t} = \alpha + \beta_{1,t}r_{m,j,t-1} + \beta_{2,t}r_{m,j,t} + \beta_{3,t}r_{m,j,t+1} + \varepsilon_{i,t}$ where $r_{i,t}$ and $r_{m,j,t}$ denote firm i's return in month t and value-weighted market return in month t, respectively.

LEADER_SPI = *SPI* of a product market leader per year. We define a firm which has the largest market share in a given industry-year as the product market leaders.

FIRM_SPI = firm's *SPI* per year.

INSIDERRET = The annual average (absolute value) of the one-month buy-and-hold excess returns (over the market) following insider trades. We only consider open market stock transactions initiated by the top five executives (CEO, CFO, COO, President, and Chairman of the Board)

LEADER_ INSIDERRET = *INSIDERVOL* of a product market leader per year. We define a firm which has the largest market share in a given industry-year as the product market leaders.

FIRM_ INSIDERRET = firm's *INSIDERVOL* per year.

INSIDERVOL = Number of shares traded by insiders in a given year divided by the total number of shares traded. We only consider open market stock transactions initiated by the top five executives (CEO, CFO, COO, President, and Chairman of the Board).

LEADER_ INSIDERVOL = *INSIDERVOL* of a product market leader per year. We define a firm which has the largest market share in a given industry-year as the product market leaders.

FIRM_ INSIDERVOL = firm's *INSIDERVOL* per year.

Table 1

Sample Distribution

Panel A: Fiscal Year

Fiscal Year	Frequency	Percent
1979	3,997	1.97
1980	4,027	1.99
1981	4,238	2.09
1982	4,290	2.12
1983	4,702	2.32
1984	4,800	2.37
1985	4,777	2.36
1986	5,016	2.48
1987	5,263	2.60
1988	5,119	2.53
1989	5,010	2.47
1990	5,015	2.48
1991	5,134	2.53
1992	5,353	2.64
1993	6,477	3.20
1994	6,856	3.38
1995	7,053	3.48
1996	7,506	3.71
1997	7,560	3.73
1998	7,232	3.57
1999	7,091	3.50
2000	6,868	3.39
2001	6,256	3.09
2002	5,840	2.88
2003	5,548	2.74
2004	5,476	2.70
2005	5,369	2.65
2006	5,273	2.6
2007	5,094	2.51
2008	4,819	2.38
2009	4,644	2.29
2010	4,545	2.24
2011	4,428	2.19
2012	4,341	2.14
2013	4,374	2.16
2014	4,491	2.22
2015	4,414	2.18
2016	4,273	2.11
Total	202,569	100.00

Panel B: Fama French 48 Industry classification

Industry	Frequency	Percent
Agriculture	622	0.31
Aircraft	970	0.48
Apparel	2,607	1.29
Automobiles and Trucks	2,903	1.43
Banking	20,278	10.01
Beer & Liquor	671	0.33
Business Services	20,350	10.05
Business Supplies	2,573	1.27
Candy & Soda	464	0.23
Chemicals	3,457	1.71
Coal	382	0.19
Communication	6,171	3.05
Computers	7,467	3.69
Construction	2,412	1.19
Construction Materials	4,785	2.36
Consumer Goods	3,337	1.65
Defense	320	0.16
Electrical Equipment	2,811	1.39
Electronic Equipment	11,240	5.55
Entertainment	2,909	1.44
Fabricated Products	753	0.37
Food Products	3,167	1.56
Healthcare	3,282	1.62
Insurance	5,239	2.59
Machinery	6,447	3.18
Measuring and Control Equipment	3,962	1.96
Medical Equipment	5,674	2.8
Non-Metallic and Industrial Metal Min..	967	0.48
Others	3,315	1.64
Personal Services	2,055	1.01
Petroleum and Natural Gas	8,962	4.42
Pharmaceutical Products	8,624	4.26
Precious Metals	1,439	0.71
Printing and Publishing	1,453	0.72
Real Estate	2,132	1.05
Recreation	1,572	0.78
Restaraunts, Hotels, Motels	3,746	1.85
Retail	9,707	4.79
Rubber and Plastic Products	1,845	0.91
Shipbuilding, Railroad Equipment	371	0.18
Shipping Containers	585	0.29
Steel Works Etc	2,655	1.31
Textiles	1,175	0.58
Tobacco Products	219	0.11
Trading	7,441	3.67
Transportation	5,307	2.62
Utilities	6,540	3.23
Wholesale	7,206	3.56
Total	202,569	100.00

Table 1 Panels A and B report the sample distribution across year and across the Fama and French (1997) industry classifications, respectively. The sample consists of 202,569 firm-year observations for a sample period from 1979 to 2016.

Table 2

Descriptive Statistics

	Product Market Leader				Other Firms					
Variable	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.	t-test p-value	Wilcoxon p-value
RDEXP	1,512	0.0194	0.0047	0.0272	201,057	0.0342	0	0.0762	***	***
LNPAT t+3	1,067	2.4872	2.5649	2.1447	122,850	0.4652	0	1.0253	***	***
LNCIT t+3	1,067	2.9209	3.2228	2.4455	122,850	0.6135	0	1.2849	***	***
Q	1,512	1.5815	1.3019	0.8795	201,057	1.8037	1.2818	1.461	***	
ASSET	1,512	9.7141	10.0055	1.3956	201,057	5.4961	5.3809	2.2892	***	***
CFO	1,512	0.1003	0.0999	0.0638	201,057	0.0429	0.063	0.1545	***	***

Table 2 reports descriptive statistics of dependent and independent variables in the regression models. The sample consists of 202,569 firm-year observations for a sample period from 1979 to 2016.All variables are defined in Appendix A.

Table 3

Product Market Power and Technological Innovation

	(1)	(2)	(3)	(7)	(8)	(9)	(1)	(2)	(3)
Dep. Variable =	RDEXP	LNPAT t+3	LNCIT t+3	RDEXP	LNPAT t+3	LNCIT t+3	RDEXP	LNPAT t+3	LNCIT t+3
LEADER_DUMMY	0.0583	0.0059	0.0074				0.0583	0.0059	0.0074
	(2.88)***	(3.04)***	(2.84)***				(2.88)***	(3.04)***	(2.84)***
LEADER_RDEXP				0.0719					
				(2.78)***					
INDMEAN_RDEXP t-1	0.2762			0.2350			0.2762		
	(2.77)***			(2.33)**			(2.77)***		
LEADER_LNPAT					0.0213				
					(5.41)***				
INDMEAN_LNPAT t-1		0.1507			0.1645			0.1507	
		(26.98)***			(28.17)***			(26.98)***	
FIRM_LNPAT t-1									
LEADER_LNCIT						0.0156			
						(3.30)***			
INDMEAN_LNCIT t-1			0.1734			0.1886			0.1734
			(22.52)***			(23.66)***			(22.52)***
FIRM_LNCIT t-1									
BOTTOM_RDEXP t-1	0.0188			0.0333			0.0188		
	(0.32)			(0.56)			(0.32)		
BOTTOM_LNPAT t-1		0.0157			0.0160			0.0157	
		(4.34)***			(4.32)***			(4.34)***	
BOTTOM_LNCIT t-1			0.0107			0.0118			0.0107
			(2.14)**			(2.32)**			(2.14)**
FIRM_Q	0.5081	0.0128	0.0166	0.5087	0.0149	0.0189	0.5081	0.0128	0.0166
	(24.87)***	(6.82)***	(6.64)***	(24.90)***	(7.69)***	(7.46)***	(24.87)***	(6.82)***	(6.64)***
FIRM_ASSET	-2.4163	0.2979	0.3439	-2.4067	0.3126	0.3626	-2.4163	0.2979	0.3439
	(-42.92)***	(53.32)***	(46.55)***	(-42.85)***	(54.59)***	(48.37)***	(-42.92)***	(53.32)***	(46.55)***
FIRM_CFO	-1.9243	-0.0067	-0.0076	-1.9246	-0.0087	-0.0097	-1.9243	-0.0067	-0.0076
	(-92.56)***	(-3.28)***	(-2.83)***	(-92.58)***	(-4.14)***	(-3.56)***	(-92.56)***	(-3.28)***	(-2.83)***
FIRM_ RDEXP_LAG1	3.3785			3.3786			3.3785		
	(110.57)***			(110.57)***			(110.57)***		
FIRM_ RDEXP_LAG2	-0.4020			-0.4014			-0.4020		
	(-15.03)***			(-15.01)***			(-15.03)***		
Observations	202,547	123,129	123,129	202,547	122,920	122,920	202,547	123,129	123,129
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Adj. R-squared	0.704	0.843	0.823	0.704	0.849	0.829	0.704	0.843	0.823

Table 3 reports regression results of testing the relationship between product market power and innovation. All variables are defined in Appendix A. t-statistics in parentheses are based on robust standard errors (Petersen, 2009). ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Table 4

Innovation-to-price sensitivities: baseline results

Dep. Variable =	RDEXP	RDEXP	LNPAT t+3	LNCIT t+3
LEADER_Q	0.1616	0.0806	0.0187	0.0130
	(4.65)***	(2.39)**	(6.24)***	(3.28)***
FIRM_Q	0.6607	0.5114	0.0106	0.0138
	(31.13)***	(25.02)***	(5.61)***	(5.54)***
LEADER_ASSET	-0.1062	-0.0947	0.0057	0.0048
	(-3.59)***	(-3.32)***	(2.10)**	(1.36)
FIRM_ASSET	-3.2112	-2.3877	0.2978	0.3457
	(-55.49)***	(-42.57)***	(53.40)***	(46.94)***
LEADER_CFO	0.1980	0.1694	-0.0128	-0.0103
	(6.63)***	(5.82)***	(-4.96)***	(-3.04)***
FIRM_CFO	-2.2165	-1.9301	-0.0077	-0.0090
	(-103.11)***	(-92.84)***	(-3.75)***	(-3.33)***
LEADER_RDEXP_LAG1		0.3122		
		(4.11)***		
FIRM_RDEXP_LAG1		3.3852		
		(111.11)***		
LEADER_ RDEXP_LAG2		-0.2767		
		(-3.68)***		
FIRM_ RDEXP_LAG2		-0.3968		
		(-14.85)***		
Observations	202,569	202,569	123,917	123,917
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Adj. R-squared	0.679	0.704	0.841	0.821

Table 4 reports regression results of testing the relationship between the stock price informativeness of product market leader and innovation. All variables are defined in Appendix A. t-statistics in parentheses are based on robust standard errors (Petersen, 2009). ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Table 5

Technological Innovation: Learning from Product Market Leader

Panel A. Product market leader's stock price non-synchronicity (SPI)

Product market leader's stock price non-syncronicity	Low	High	Low	High	Low	High
Dep. Variable =	RDEXP	RDEXP	LNPAT t+3	LNPAT t+3	LNCIT t+3	LNCIT t+3
LEADER_Q	-0.2289	0.2450	0.0181	0.0549	0.0100	0.0657
	(-5.47)***	(5.42)***	(2.70)***	(5.69)***	(1.14)	(5.30)***
DIFF	0.4739		0.0368		0.0557	
	(7.77)***		(3.21)***		(3.82)***	
FIRM_Q	0.1809	0.1568	0.0124	0.0269	0.0114	0.0383
	(7.43)***	(6.44)***	(2.79)***	(4.70)***	(1.96)**	(5.20)***
DIFF	-0.0241		0.0145		0.0269	
	(-0.43)		(2.07)**		(3.03)***	
Firm-level controls	YES	YES	YES	YES	YES	YES
Observations	49,711	40,339	28,947	29,345	28,947	29,345
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	69,824	71,220	43,794	44,466	43,794	44,466
Adj. R-squared	0.861	0.886	0.849	0.718	0.832	0.698

Panel B. Product market leader's insider trading return

Firm's insider trading return	Low	High	Low	High	Low	High
Dep. Variable =	RDEXP	RDEXP	LNPAT t+3	LNPAT t+3	LNCIT t+3	LNCIT t+3
LEADER_Q	-0.1633	0.2223	0.0118	0.0124	0.0054	0.0196
	(-2.69)***	(2.76)***	(2.71)***	(1.97)**	(0.91)	(2.47)**
DIFF	0.3856		0.0006		0.0142	
	(3.20)***		(0.12)		(2.09)**	
FIRM_Q	0.3954	0.8345	0.0104	0.0217	0.0160	0.0301
	(14.16)***	(13.30)***	(4.76)***	(4.32)***	(5.46)***	(4.73)***
DIFF	0.4391		0.0113		0.0141	
	(6.74)***		(2.15)**		(2.07)**	
Firm-level controls	YES	YES	YES	YES	YES	YES
Observations	107,274	36,553	70,226	20,665	70,226	20,665
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.665	0.757	0.816	0.868	0.815	0.853

Table 5 *Continued.*

Panel C. Product market leader's insider trading volume

Firm's insider trading return	Low	High	Low	High	Low	High
Dep. Variable =	RDEXP	RDEXP	LNPAT t+3	LNPAT t+3	LNCIT t+3	LNCIT t+3
LEADER_Q	-0.1745	0.1370	0.0157	0.0158	0.0103	0.0238
	(-2.92)***	(1.80)*	(3.38)***	(2.72)***	(1.70)*	(3.24)***
DIFF	0.3115		0.0001		0.0135	
	(3.47)***		(0.01)		(2.07)**	
FIRM_Q	0.3968	0.7121	0.0212	0.0205	0.0305	0.0318
	(14.20)***	(12.27)***	(9.07)***	(4.56)***	(9.99)***	(5.57)***
DIFF	0.3153		-0.0007		0.0013	
	(5.18)***		(-0.14)		(0.21)	
Firm-level controls	YES	YES	YES	YES	YES	YES
Observations	107,106	36,343	74,120	34,188	74,120	34,188
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.664	0.765	0.770	0.775	0.756	0.760

Table 5 reports regression results of testing the relationship between the stock price informativeness of product market leader and innovation, conditioning on a leader's private information flow. The leader's private information flow is captured by stock price non-synchronicity, insider trading return and volume in Panel A, B and C, respectively. SPI is a measure of firm-specific information arriving to the security market based on R2 from the augmented market model regression. Specifically, SPI = $\ln((1 - R^2)/ R^2)$. Firm-Specific Weekly Return is equal to ln(1+residual), where the residual is from the augmented market model regression: $r_{i,t} = \alpha + \beta_{1,t}r_{m,j,t-1} + \beta_{2,t}r_{m,j,t} + \beta_{3,t}r_{m,j,t+1} + \varepsilon_{i,t}$. Insider trading return is calculated as the annual average (absolute value) of the one-month buy-and-hold excess returns (over the market) following insider trades. We only consider open market stock transactions initiated by the top five executives (CEO, CFO, COO, President, and Chairman of the Board). Insider trading volume is measured by the number of shares traded by insiders in a given year divided by the total number of shares traded. All variables are defined in Appendix A. *t*-statistics in parentheses are based on robust standard errors (Petersen, 2009). ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Table 6

Tobin's Q of Product Market Leader and Innovation, Conditioning on Managerial Information Demand

Panel A. Firm's stock price non-syncronicity

Firm's stock price non-syncronicity	Low	High	Low	High	Low	High
Dep. Variable =	RDEXP	RDEXP	LNPAT t+3	LNPAT t+3	LNCIT t+3	LNCIT t+3
LEADER_Q	0.0964	-0.1140	0.0097	0.0064	0.0123	-0.0044
	(2.59)***	(-4.51)***	(2.13)**	(0.80)	(1.88)*	(-0.44)
DIFF	-0.2104		-0.0033		-0.0167	
	(-4.72)***		(-0.50)		(-2.02)**	
FIRM_Q	-0.0001	0.1927	0.0084	0.0265	0.0137	0.0373
	(-0.56)	(8.15)***	(2.66)***	(4.75)***	(3.05)***	(5.35)***
DIFF	0.1928		0.0181		0.0236	
	(2.59)***		(2.86)***		(2.91)***	
Firm-level controls	YES	YES	YES	YES	YES	YES
Observations	58,675	58,649	34,200	41,533	34,200	41,533
Year FE	0.904	0.891	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	YES	YES	0.725	0.815	0.690	0.804

Panel B. Firm insider trading return

Firm's insider trading return	Low	High	Low	High	Low	High
Dep. Variable =	RDEXP	RDEXP	LNPAT t+3	LNPAT t+3	LNCIT t+3	LNCIT t+3
LEADER_Q	0.1718	-0.0860	0.0177	0.0052	0.0117	0.0029
	(3.91)***	(-0.89)	(4.35)***	(0.89)	(2.18)**	(0.35)
DIFF	-0.2578		-0.0125		-0.0088	
	(-2.68)***		(-2.03)**		(-1.67	
FIRM_Q	0.4336	0.51)*42	0.0180	0.0112	0.0253	0.0208
	(16.65)***	(9.81)***	(7.38)***	(3.35)***	(7.85)***	(4.41)***
DIFF	0.0806		-0.0068		-0.0045	
	(1.40)		(-1.69)*		(-0.80)	
Firm-level controls	YES	YES	YES	YES	YES	YES
Observations	121,802	43,498	85,811	27,980	85,811	27,980
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.726	0.661	0.821	0.764	0.799	0.747

Table 6

Continued.

Panel C. Firm insider trading volume

Firm's insider trading return	Low	High	Low	High	Low	High
Dep. Variable =	RDEXP	RDEXP	LNPAT t+3	LNPAT t+3	LNCIT t+3	LNCIT t+3
LEADER_Q	0.1531	-0.0813	0.0177	0.0050	0.0119	0.0034
	(3.70)***	(-1.41)	(4.41)***	(0.79)	(2.25)**	(0.39)
DIFF	-0.2344		-0.0127		-0.0085	
	(-3.47)***		(-2.00)**		(-1.72)	
FIRM_Q	0.4038	0.6166	0.0186	0.0134	0.0255	0.0239
	(16.30)***	(17.23)***	(7.65)***	(4.35)***	(7.94)***	(5.59)***
DIFF	0.2128		-0.0052		-0.0016	
	(5.10)***		(-1.36)		(-0.31)	
Firm-level controls	YES	YES	YES	YES	YES	YES
Observations	123,291	64,627	86,654	40,729	86,654	40,729
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.735	0.752	0.821	0.755	0.799	0.741

Table 6 reports regression results of testing the relationship between the stock price informativeness of product market leader and innovation, conditioning on the following firms' private information flow. The following firms' private information flow is captured by stock price non-synchronicity, insider trading return and volume in Panel A, B and C, respectively. SPI is a measure of firm-specific information arriving to the security market based on R2 from the augmented market model regression. Specifically, SPI = $\ln((1 - R^2)/ R^2)$. Firm-Specific Weekly Return is equal to ln(1+residual), where the residual is from the augmented market model regression: $r_{i,t} = \alpha + \beta_{1,t}r_{m,j,t-1} + \beta_{2,t}r_{m,j,t} + \beta_{3,t}r_{m,j,t+1} + \varepsilon_{i,t}$. Insider trading return is calculated as the annual average (absolute value) of the one-month buy-and-hold excess returns (over the market) following insider trades. We only consider open market stock transactions initiated by the top five executives (CEO, CFO, COO, President, and Chairman of the Board). Insider trading volume is measured by the number of shares traded by insiders in a given year divided by the total number of shares traded. All variables are defined in Appendix A. *t*-statistics in parentheses are based on robust standard errors (Petersen, 2009). ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Table 7

Technological Innovation: Learning from Product Market Leader: Economic Channels

Panel A. Institutional Ownership

Institutional Ownership =	The Lowest Tercile	The Highest Tercile	The Lowest Tercile	The Highest Tercile	The Lowest Tercile	The Highest Tercile
Dep. Variable =	RDEXP	RDEXP	LNPAT t+3	LNPAT t+3	LNCIT t+3	LNCIT t+3
LEADER_Q	0.2866	-0.1504	0.0322	0.0199	0.0331	0.0194
	(5.21)***	(-4.19)***	(6.13)***	(3.16)***	(4.63)***	(2.34)**
DIFF (Highest - Lowest)	-0.4370		-0.0123		-0.0137	
	(-6.83)***		(-1.66)*		(-1.28)	
FIRM_Q	0.2789	0.3471	0.0161	0.0132	0.0255	0.0237
	(8.30)***	(14.17)***	(4.84)***	(2.88)***	(5.64)***	(3.93)***
DIFF (Highest - Lowest)	0.0682		-0.0029		-0.0018	
	(1.68)*		(-0.53)		(-0.24)	
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,382	67,522	41,531	40,532	41,531	40,532
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
IND FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.821	0.837	0.802	0.790	0.775	0.779

Panel B. Product Similarity

Product Similarity =	The Lowest Tercile	The Highest Tercile	The Lowest Tercile	The Highest Tercile	The Lowest Tercile	The Highest Tercile
Dep. Variable =	RDEXP	RDEXP	LNPAT t+3	LNPAT t+3	LNCIT t+3	LNCIT t+3
LEADER_Q	-0.6404	0.1522	0.0127	0.0117	-0.0009	0.0190
	(-5.56)***	(2.66)***	(1.61)	(2.87)***	(-0.08)	(3.68)***
DIFF (Highest - Lowest)	0.7926		-0.0010		0.0199	
	(6.22)***		(-0.12)		(2.91)***	
FIRM_Q	0.3449	0.7481	0.0085	0.0287	0.0164	0.0300
	(9.47)***	(15.63)***	(3.18)***	(7.26)***	(4.30)***	(5.98)***
DIFF (Highest - Lowest)	0.4032		0.0202		0.0136	
	(6.78)***		(4.34)***		(2.20)**	
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	71,339	53,758	42,298	28,623	42,298	28,623
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
IND FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.650	0.764	0.802	0.884	0.788	0.866

Panel C. R&D intensive industries

R&D intensive industries =	The Lowest Tercile	The Highest Tercile	The Lowest Tercile	The Highest Tercile	The Lowest Tercile	The Highest Tercile
Dep. Variable =	RDEXP	RDEXP	LNPAT t+3	LNPAT t+3	LNCIT t+3	LNCIT t+3
LEADER_Q	0.0004	0.2002	0.0002	0.0146	-0.0024	0.0051

	(0.02)	(2.33)**	(0.10)	(2.29)**	(-0.66)	(0.62)
DIFF (Yes-No)	0.1998		0.0144		0.0075	
	(2.39)**		(2.24)**		(0.95)	
FIRM_Q	0.1610	0.8687	-0.0013	0.0265	-0.0036	0.0323
	(9.83)***	(18.54)***	(-0.52)	(7.19)***	(-0.99)	(6.72)***
DIFF (Yes-No)	0.7077		0.0278		0.0359	
	(14.60)***		(6.89)***		(6.02)***	
Observations	70,117	58,674	42,385	37,705	42,385	37,705
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
IND FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.566	0.700	0.624	0.855	0.584	0.832

Panel D. **Industry Cash Flow Volatility**

Cash Flow Volatility =	The Lowest Tercile	The Highest Tercile	The Lowest Tercile	The Highest Tercile	The Lowest Tercile	The Highest Tercile
Dep. Variable =	RDEXP	RDEXP	LNPAT t+3	LNPAT t+3	LNCIT t+3	LNCIT t+3
LEADER_Q	-0.2002	0.1841	-0.0020	0.0198	-0.0033	0.0187
	(-2.07)**	(2.80)***	(-0.42)	(2.78)***	(-0.53)	(1.94)*
DIFF (Highest - Lowest)	0.3843		0.0218		0.022	
	(3.46)***		(2.68)***		(2.03)**	
FIRM_Q	0.8330	0.2406	0.0073	0.0130	0.0123	0.0218
	(16.68)***	(6.18)***	(1.48)	(3.23)***	(1.89)*	(3.99)***
DIFF (Highest - Lowest)	-0.5924		0.0057		0.0095	
	(-9.65)***		(0.91)		(1.16)	
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,844	49,823	32,582	29,615	32,582	29,615
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
IND FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.787	0.840	0.818	0.824	0.802	0.809

Table 7 reports regression results of testing the impact of managerial informational demand on the positive relationship between the market valuation of product market leader and innovation. The level managerial informational demand is captured by the following firms' institutional ownership, product similarity, industry R&D intensity, and cash flow volatility in Panels A, B, C, and D, respectively. The level of firm institutional ownership is measured by the ownership percentage held by institutional investors in a given year. The level of product similarity is measured by the level of product similarity between a leader and other firms in an industry (Hoberg & Phillips, 2016). The level of industry R&D intensity is measured by the industry mean of *RDEXP* in a given year. The level of industry cash flow volatility is measured by the industry mean of the standard deviation of cash flow for three years. All variables are defined in Appendix A. *t*-statistics in parentheses are based on robust standard errors (Petersen, 2009). ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Table 8

Peers' Mimicking Behavior, Conditioning on the Stock Return around Industry Leader's Patent Grant Date

Dep. Variable =	INDUSTRY PEER RDA	INDUSTRY PEER RDA
LEADER_RET3	0.0539**	
	(2.33)	
LEADER_RET5		0.0119**
		(2.04)
LEADER_ASSET	-0.0007**	0.0001
	(-2.03)	(0.33)
FIRM_ASSET	-0.0068***	-0.0052***
	(-16.82)	(-17.80)
LEADER_CFO	0.0145***	0.0119***
	(10.36)	(7.64)
FIRM_CFO	-0.1408***	-0.1062***
	(-44.38)	(-23.57)
LEADER_RDEXP_LAG1	-0.0091*	-0.0049***
	(-1.84)	(-4.38)
FIRM_RDEXP_LAG1	0.1583***	0.1526***
	(45.92)	(41.19)
LEADER_ RDEXP_LAG2	0.0115**	-0.0034***
	(2.31)	(-2.66)
FIRM_ RDEXP_LAG2	0.0198***	0.0279***
	(9.80)	(13.37)
Observations	414,585	414,585
Year FE	YES	YES
Firm FE	YES	YES
Adj. R-squared	0.537	0.533

Table 8 reports regression results of examining the industry peers' mimicking behavior of product market leader's innovation, conditional on the stock returns around the product market leader's patent grant date. *LEADER_RET3* denotes 3-day cumulative excess return around the product market leader's patent grant date. Daily excess return is calculated as the raw daily return minus the daily return on a value-weighted market portfolio. *MOM* denotes the market-adjusted compounded daily return over the prior six months. *SIZE* denotes the natural log of a firm's total assets. *BM* is calculated as total assets divided by (total assets – book value of common/ordinary equity + market value of equity). All variables are defined in Appendix A. *t*-statistics in parentheses are based on robust standard errors (Petersen, 2009). ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Table 9

Mimicry of Innovation Investments

	RDEXP	RDEXP	LNPAT t+3	LNPAT t+3	LNCIT t+3	LNCIT t+3
LEADER_INNOVt-1	0.0859	-0.2245	0.0463	0.0418	0.0381	0.0377
	(3.37)***	(-3.62)***	(12.05)***	(6.85)***	(8.28)***	(4.74)***
LEADER_SPI t-1		-0.1017		-0.0057		-0.0093
		(-2.78)***		(-1.19)		(-1.47)
LEADER_INNOV t-1 × LEADER_SPI t-1		0.0847		0.0089		0.0105
		(3.48)***		(3.68)***		(3.35)***
FIRM_Q	0.5083	0.4941	0.0128	0.0108	0.0163	0.0139
	(24.89)***	(19.82)***	(6.60)***	(4.44)***	(6.41)***	(4.38)***
FIRM_ASSET	-2.3930	-2.9310	0.3136	0.3693	0.3652	0.4331
	(-42.67)***	(-40.23)***	(54.68)***	(48.83)***	(48.71)***	(43.82)***
FIRM_CFO	-1.9268	-2.1416	-0.0104	-0.0117	-0.0118	-0.0146
	(-92.73)***	(-84.40)***	(-4.97)***	(-4.45)***	(-4.30)***	(-4.25)***
FIRM_ RDEXP_LAG1	3.3888	3.5029				
	(111.22)***	(97.02)***				
FIRM_ RDEXP_LAG2	-0.3960	-0.3725				
	(-14.82)***	(-11.67)***				
Observations	136,703	136,703	80,605	80,605	80,605	80,605
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.704	0.736	0.847	0.851	0.828	0.830

Table 9 reports regression results of testing the mimicry of product market leader's innovation by its following firms. All variables are defined in Appendix A. t-statistics in parentheses are based on robust standard errors (Petersen, 2009). ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Table 10

Tobin's Q of Product market leader and Future Operating Performance

VARIABLES	Profitability t+3	CFO t+3	Profitability t+3	CFO t+3
LEADER_Q	-0.3179	-0.2913	-0.3366	-0.3077
	(-2.53)**	(-2.82)***	(-2.67)***	(-2.98)***
LEADER_SPI	-0.5446	-0.3544	-0.5763	-0.3822
	(-5.02)***	(-3.98)***	(-5.29)***	(-4.27)***
LEADER_Q* LEADER_SPI	0.2932	0.1783	0.2995	0.1841
	(5.63)***	(4.17)***	(5.75)***	(4.31)***
FIRM_Q	0.4834	0.5761	0.5149	0.6066
	(8.25)***	(11.97)***	(8.78)***	(12.60)***
LEADER_ASSET	-0.5197	-0.2566	-0.2851	-0.0451
	(-3.51)***	(-2.11)**	(-1.76)*	(-0.34)
FIRM_ASSET	-3.7907	-0.1372	-3.9927	-0.3334
	(-22.39)***	(-0.99)	(-23.44)***	(-2.38)**
LEADER_CFO	-0.0027	0.0575	-0.0814	-0.0134
	(-0.03)	(0.82)	(-0.93)	(-0.19)
FIRM_CFO	1.3184	0.9833	1.4389	1.1004
	(21.46)***	(19.49)***	(23.01)***	(21.44)***
LEADER_LEV			-0.3685	-0.3325
			(-3.62)***	(-3.97)***
FIRM_LEV			0.7449	0.7228
			(10.27)***	(12.13)***
Observations	100,865	100,865	100,865	100,865
Year FE	0.571	0.595	0.572	0.595
FIRM FE	YES	YES	YES	YES
Adj. R-squared	YES	YES	YES	YES

Table 10 reports regression results of testing the impact of the Stock Price Informativeness of Product market leader on future operating performance for a given firm. All variables are defined in Appendix A. *t*-statistics in parentheses are based on robust standard errors (Petersen, 2009). ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Table 11
Fund Flow Volatility Pressure

VARIABLES	RDEXP	RDEXP	LNPAT t+3	LNCIT t+3
LEADER_MFFLOWVOL	-0.0308	0.0006	-0.0058	-0.0084
	(-1.09)	(0.02)	(-2.37)**	(-2.57)**
FIRM_MFFLOWVOL	-0.0765	-0.0612	-0.0033	-0.0026
	(-4.72)***	(-3.93)***	(-2.27)**	(-1.36)
LEADER_ASSET	-0.0605	-0.0607	0.0093	0.0036
	(-1.78)*	(-1.84)*	(3.00)***	(0.87)
FIRM_ASSET	-3.5698	-2.6532	0.2917	0.3381
	(-62.06)***	(-47.55)***	(52.69)***	(46.26)***
LEADER_CFO	0.2484	0.1874	-0.0055	-0.0057
	(9.68)***	(7.33)***	(-2.45)**	(-1.90)*
FIRM_CFO	-2.1702	-1.8901	-0.0069	-0.0079
	(-100.97)***	(-91.04)***	(-3.41)***	(-2.94)***
LEADER_RDEXP_LAG1		0.3249		
		(4.27)***		
FIRM_RDEXP_LAG1		3.4182		
		(112.11)***		
LEADER_ RDEXP_LAG2		-0.2793		
		(-3.70)***		
FIRM_ RDEXP_LAG2		-0.3838		
		(-14.34)***		
Observations	202,569	202,569	123,917	123,917
Year FE	0.678	0.703	0.841	0.821
FIRM FE	YES	YES	YES	YES
Adj. R-squared	YES	YES	YES	YES

Table 11 reports regression results of testing the impact of the mutual fund flow volatility pressure of product market leader on a firm's innovation. All variables are defined in Appendix A. *t*-statistics in parentheses are based on robust standard errors (Petersen, 2009). ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.