# Yesterday's enemy is today's friend: Innovation externalities, follow-on innovation, and insider sales

Yun Ju Cha, Konan Chan, and Baek-Chun Kim *

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**Abstract**

We develop a novel approach to identifying which firms transform competitor innovations into follow-on innovation and which fail to adapt. Our method exploits the information embedded in insider trading behavior: insider silence following competitor innovation signals confidence in the firm's capacity to build on external knowledge, while insider sales signal vulnerability to displacement. Using patent-based measures of competitor innovation value, we find that competitor innovations trigger insider sales profits on average, consistent with a negative private assessment. These effects are stronger when product market competition is higher, insiders face greater income risk, and firms have lower long-term investment. Exploiting the 2008 Federal Circuit ruling—which strengthened employers' patent rights in certain states—as an exogenous shock, we confirm that competitor innovations causally affect insider responses. Firms identified via insider silence subsequently increase patenting and trade secrecy whereas insider-selling firms experience reduced sales growth. Knowledge spillovers drive these patterns, but only for firms signaled by insider silence. Our findings show that insider trading behavior provides a simple, observable ex ante indicator of firm resilience to external technological shocks and capacity for cumulative innovation, offering new insights into the heterogeneity of innovation-driven competition.

**Keywords**: Innovation, Knowledge spillovers, Negative externality, Insider trading, Patent disclosure

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* Yunju Cha and Konan Chan are from the Department of Finance, the College of Commerce, National Chengchi University, Taiwan (E-mail: yjcha@nccu.edu.tw; konan@nccu.edu.tw); Baek-Chun Kim is from the Department of Money and Banking, the College of Commerce, National Chengchi University, Taiwan (baekchun@nccu.edu.tw). We thank Dimitris Papanikolaou, Utpal Bhattacharya, Morten Bennedsen, Kevin Tseng, Yanzhi (Andrew) Wang, Jungmin Kim, Hui-Ching Chuang (discussant), Wei Li, Douglas Cheng, Mike Weng, Wenbin Hu (discussant), seminar participants at the 2025 Annual meeting of the Asia Finance Association, the 2025 Annual meeting of the Taiwan Finance Association, and Chulalongkorn University for their helpful comments. All errors are our own. Baek-Chun Kim is the corresponding author. This paper was previously circulated under the title "Profitability of insider trading against innovation by competitors." Yunju Cha gratefully acknowledges research support from the National Science and Technology Council, Taiwan (NSTC 112-2410-H-004-118-). Konan Chan appreciates financial support from the National Science and Technology Council, Taiwan (NSTC 112-2410-H-004-100-MY3). Baek-Chun Kim acknowledges research support from the National Science and Technology Council, Taiwan (NSTC 114-2410-H-004-078-).

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## 1. Introduction

Innovation lies at the heart of firm dynamics and long-run economic growth. Foundational theories of endogenous growth (Romer, 1986, 1990; Lucas, 1988) and creative destruction (Schumpeter, 1942) emphasize that technological progress operates through two forces: the creation of new knowledge that spills over to other firms and industries, and the displacement of existing products, technologies, and business models. The public disclosure of ideas, particularly through patents, has been shown to stimulate cumulative innovation by making knowledge more widely accessible (Jaffe, 1986; Hall, Jaffe, and Trajtenberg, 2005; Bloom, Schankerman, and Van Reenen, 2013; Kim and Valentine, 2021; Tseng and Zhong, 2024).[1, 2] At the same time, new ideas often impose negative externalities on other firms by eroding competitive advantage, reducing cash flows, and undermining organizational capabilities. These displacement effects are documented in a range of settings (Aghion and Howitt, 1992; Autor and Dorn, 2013; Kogan et al., 2017; Acemoglu and Restrepo, 2020; Braxton and Taska, 2023).[3]

In practice, every major innovation simultaneously generates both positive and negative externalities. A competitor's patent may represent an existential threat to an incumbent's products,

[1] Jaffe (1986) finds an R&D spillover effect where R&D in neighboring high-technology firms increase R&D productivity. Jaffe, Trajtenberg, and Henderson (1993) show that knowledge spillovers are localized, finding that a given patent is more likely to be cited by other firms operating in the same location as a focal firm (e.g., a state). Bloom, Schankerman, and Van Reenen (2013) find that positive spillovers exist when firms share the same technological space in a market. Kim and Valentine (2021) find that knowledge spillovers drive follow-on innovation if patent disclosure by peers occurs more quickly after the American Inventors Protection Act (AIPA) took effect. Tseng and Zhong (2024) show that similar financial reporting increases cross-citations as well as follow-on innovations.

[2] Romer (1990) documents two features that distinguish technology from conventional economic goods: non-rivalry and partial excludability. Non-rivalry means that the use of intellectual property by one firm or person in no way limits its use by another. Partial excludability means that even incomplete use of intellectual property prevents others from using it. Glaeser and Lang (2024) document such features and their implications for the accounting literature.

[3] Autor and Dorn (2013), Acemoglu and Restrepo (2020), and Braxton and Taska (2023) document that technological change (e.g., automation, robotics) affects labor markets through wages, polarization, and job losses. Kogan et al. (2017) show that the value of competitor innovations reduces the future value of fundamentals (e.g., productivity) for focal firms.

yet at the same time disclose information that could be repurposed to improve the incumbent's own innovation. Whether competitor innovation is ultimately harmful or beneficial depends on the focal firm's absorptive capacity, strategic flexibility, and financial position (Aghion et al., 2005; Bloom, Schankerman, and Van Reenen, 2013; Zhang, 2019; Kogan, Papanikolaou, and Stoffman, 2020; Tseng, 2022; Knesl, 2023). Firms with limited capacity to respond may suffer value destruction, while those able to learn from competitors may turn the same external innovation into an opportunity for follow-on innovation. This heterogeneity is a core feature of innovation-driven competition, yet we know relatively little about how to identify ex ante which firms experience a competitor's innovation as a threat and which as a source of opportunity.

In this paper, we develop a novel approach to address this question by exploiting the information embedded in insider trading behavior. The key insight is that the way corporate insiders trade around competitor innovations reveals their private assessment of how those innovations affect their own firm's prospects. A large literature shows that insider transactions contain valuable information about future stock returns (Jaffe, 1974; Finnerty, 1976; Seyhun, 1986; Rozeff and Zaman, 1988; Lakonishok and Lee, 2001; Cohen, Malloy, and Pomorski, 2012). When insiders choose to sell in the wake of a competitor innovation, this decision is likely to reflect a negative private view of the impact on the firm (Tookes, 2008). Conversely, when exposed insiders remain silent—that is, when they do not reduce their holdings despite new risks to the firm's competitive position—their inaction suggests private confidence that their firm can withstand, or even benefit from, the innovation shock. Such silence restricts the dissemination of proprietary information, and lead to follow-on innovation (Choi, Faurel, and Hillegeist, 2025). We use these patterns of insider response to competitor innovation as an informative signal of how different firms experience external technological shocks.

Our empirical strategy proceeds in three steps. First, following Kogan et al. (2017), we measure competitor innovations using the stock market value of patents at the time of grant, which captures the market's assessment of their technological and economic significance. For each firm, we construct an external innovation shock by aggregating the patent value of competitors (hereafter *Innovation by competitors*).[4] Second, we analyze insider trading behavior in the focal firm following these competitor innovation shocks, focusing on the intensive margin of insider sales. Finally, we link this variation in insider response to subsequent outcomes in firm performance and innovation.

This approach yields three main sets of results. First, competitor innovations induce a significant profitability in insider sales. Insiders exposed to a competitor's innovation tend to reduce their equity holdings, and these sales are associated with positive abnormal returns[5], consistent with insiders acting on private information about deteriorating prospects. The effect is strongest in settings where displacement effects are likely to be severe: industries with high product market competition, firms led by executives whose compensation is highly sensitive to stock prices, and firms that have low investment or are financially constrained. Notably, we find little evidence of offsetting insider purchases after competitor innovation, indicating that insider response is asymmetric: insiders primarily use their private information defensively.

Second, and more importantly for our purposes, not all firms exhibit insider sales in response to competitor innovation. For a substantial share of firms, insider trading activity remains unchanged. These "silent" firms behave very differently in the aftermath of competitor innovation.

[4] We define competitors as firms in the same three-digit SIC industry family. Our results are robust when we define competitors using TNIC as in Hoberg and Philips (2016).

[5] For ease of interpretation, we multiply -1 by the profitability of sales transactions. So, positive sales transaction profits indicate that insiders have avoided potential losses from negative information or news.

Unlike selling firms, they do not experience declines in sales growth. Instead, they increase their own innovation efforts, as measured by subsequent patenting and greater reliance on trade secrecy. This pattern suggests that insider silence reflects an internal assessment that the firm is capable of adapting to and building upon the competitor's innovation, rather than being displaced by it.

Third, we explore the mechanism linking insider silence to follow-on innovation. Using a Jaffe-style measure of technological proximity (Jaffe, 1986; Bloom, Schankerman, and Van Reenen, 2013), we show that knowledge spillovers from competitor innovation are positively associated with subsequent innovation only for firms whose insiders do not sell. Among selling firms, knowledge spillovers appear to be of little value. These results imply that insider silence effectively identifies firms with the absorptive capacity to transform external knowledge into cumulative innovation. Turning to trade secrecy, firms use it strategically to limit knowledge dissemination (Glaeser, 2018; Chang, Tseng, and Yu, 2024). When proprietary information derives from knowledge spillover, they may rely less on secrecy as competitor innovations have already been disclosed. Consistent with this view, silent firms initially increase their use of trade secrecy—shielding integration of competitor knowledge from disclosure—and subsequently reduce secrecy as new innovation is formalized through peers' patents.

To provide further evidence on causality, we exploit a quasi-natural experiment based on a 2008 Federal Circuit court decision that differentially increased the strength of patent rights in some states. Following this exogenous increase in competitor innovation, firms exposed to competitors from the affected states exhibited a pronounced rise in insider profitability. This setting confirms that competitor innovations trigger information-driven insider trading, and that the absence of insider selling is informative about the firm's ability to respond productively.

Our findings contribute to several strands of the literature. First, we provide new evidence on the dual nature of innovation externalities. While prior research has documented either positive spillovers (e.g., Jaffe, 1986; Bloom, Schankerman, and Van Reenen, 2013) or negative displacement effects (e.g., Kogan et al., 2017; Kogan, Papanikolaou, and Stoffman, 2020) separately, we show that both forces operate simultaneously, and that insider behavior reveals which force dominates for a given firm. This insight helps reconcile seemingly contradictory findings in the literature on innovation and competition.

Second, we advance the literature on cumulative innovation by showing that the ability to benefit from spillovers is not uniform (Bloom, Schankerman, and Van Reenen, 2013; Kogan, Papanikolaou, and Stoffman, 2020; Tseng, 2022). Firms differ markedly in their capacity to transform competitor disclosures into valuable follow-on innovation. Our approach provides a simple and observable way—through insider responses—to identify these firms ex ante. In doing so, we highlight a previously unexplored behavioral mechanism linking competitor innovation to firm-level outcomes.

Third, we contribute to the literature on insider trading. The prior studies show that insider sales are informative if the source of information is public but inattentive (Alldredge and Cicero, 2015).[6] Also, the recent work highlights that insider transactions are shaped by proprietary information (Choi, Faurel, and Hillegeist, 2025; Guest et al., 2025). Building on these findings, our results show that in the specific context of competitor innovation shocks, insider sales are highly informative. More importantly, the absence of sales—the decision to remain silent—carries significant information about a firm's future performance and innovation activity. These findings

[6] The literature show that insider purchases are more informative than sales because sales are often driven by diversification or liquidity needs (Lakonishok and Lee, 2001; Dai et al., 2016). Also, the sales transaction faces higher litigation costs (Cheng and Lo, 2006; Rogers, 2008).

open a new perspective on how insider trading data can be used to study firm strategy and expectations.

Finally, this paper complements work on the strategic interaction between firms in innovative industries. Recent research emphasizes the importance of external ideas for firm performance and the mechanisms through which knowledge flows across firm boundaries (e.g., Bernstein, 2015; Seru, 2014; Ederer and Manso, 2013). Our findings indicate that the market's most informed participants—the firms' own insiders—react strongly to competitor innovation, and that their reactions can be used to infer the competitive positioning and innovative potential of the firm.

The rest of the paper is organized as follows. Section 2 reviews related literature and develops our empirical predictions. Section 3 describes the data and variable construction. Section 4 presents the main results on insider trading responses to competitor innovations, and Section 5 examines the implications for firm outcomes and mechanisms. Section 6 concludes.

## 2. Main hypothesis development

Innovation generates both positive and negative externalities. On the positive side, patents disseminate knowledge through partial excludability[7], enabling cumulative and follow-on innovation, namely knowledge spillover (Jaffe, 1987; Romer, 1990; Bloom, Schankerman, and Van Reenen, 2013; Zhong, 2018; Tseng and Zhong, 2024). On the negative side, valuable innovations protect their advantage by reducing future profitability for or by discouraging

[7] While patent filing grants inventors partial excludability for legal protections of their patents in exchange for disclosure, the USPTO requires patent disclosures to include sufficient details and to be publicly available. This allows someone who is skilled in the relevant area to recreate the innovation independently of the original inventor (35 USC § 112(a)). This makes knowledge spillover an intended consequence of patent disclosure. See Glaeser and Lang (2024) for the detail.

investments by peers, creating displacement and obsolescence risks (Aghion and Howitt, 1992; Gârleanu, Kogan, and Panageas, 2012; Kogan et al., 2017; Zhang, 2019; Acemoglu and Restrepo, 2022; Braxton and Taska, 2023). Such negative externalities decrease follow-on innovation (Bloom, Schankerman, and Van Reenen, 2013; Kogan, Papanikolaou, and Stoffman, 2020).

However, whether competitor innovation is harmful or beneficial depends on the focal firm's absorptive capacity and strategic flexibility (Bloom, Schankerman, and Van Reenen, 2013; Zhang, 2019; Kogan, Papanikolaou, and Stoffman, 2020; Tseng, 2022; Knesl, 2023). Negative externalities reallocate resources away from less productive firms and toward more productive firms, thereby shaping the process of follow-on innovation. Also, firms with limited capacity to respond may suffer value destruction, while those able to learn from competitors may turn the same external innovation into an opportunity for follow-on innovation. This heterogeneity is a core feature of innovation-driven competition and industry dynamics, but we know little about how to identify ex ante which firms experience a competitor's breakthrough as a threat and which as a source of opportunity.

### 2.1 Insider trading as an identification strategy

We develop a novel approach to address this question by exploiting the information embedded in insider trading behavior. We argue that inside transactions are informative, making it possible to identify how firms react to two countervailing externalities. Inside transactions release private information to financial markets (Jaffe, 1975; Finnerty, 1976; Rozeff, and Zaman, 1988; Ravina and Sapienza, 2009; Cohen et al., 2012). Most firms adopt insider trading policies to protect proprietary information, and those facing high proprietary costs discourage or prohibit their managers from exploiting proprietary information through insider trading (Choi, Faurel, and Hillegeist, 2025). If insiders know that their firms are not severely affected by the negative externality of competitor innovation because they can create follow-on innovations, they hold onto their proprietary information and remain silent with respect to insider trading. If insiders possess the private information about damage that might be caused by competitor innovation, however, they will exploit their information advantage to earn significant profits from sales transactions.

Our argument assumes that negative externalities indeed affect the behavior of insiders. A marketable competitor innovation threatens future earnings for top workers (Kogan et al., 2021) as well as firm value (Kogan et al., 2017; Kogan, Papanikolaou, and Stoffman, 2020). This suggests that insiders, defined under SEC regulations as officers, directors, or large shareholders, are highly exposed to the negative externality of competitor innovation and therefore have a strong motive to hedge against such innovation. Additionally, insiders are able to evaluate the future damage that competitor innovation could cause using their private information and trade stocks based on their information advantage (Tookes, 2008).[8] Given an insider's strong motives and superior information, we hypothesize that, when an insider receives competitor innovation news, she earns trading profits by updating and exploiting private information her firm holds to hedge against competitor innovation. Therefore, we propose our main hypothesis:

**Hypothesis 1**. Insiders sell shares in their firms after competitor innovations are announced and the profitability of such transactions is significantly positive.

While prior studies find that insider sales are uninformative, we argue that they are informative in our setting for two reasons. First, insider sales are generally not profitable due to litigation risk (Cheng and Lo, 2006; Rogers, 2008), yet sales can be profitable when they exploit

[8] Tookes (2008) proposes a Cournot-Nash equilibrium model where an insider observes private information about her firm's future costs and exploits it to make profits by trading either her firm's stock or competitor stocks. Tookes further shows that an insider engages in informed trading after observing an industry-wide shock. Because such industry-wide shocks include competitor innovation, an insider trades her firm's stock or competitor stocks to hedge against this displacement-risk news.

public but neglected information (Alldredge and Cicero, 2015). In our context, insiders rely on publicly available information—the value of competitor innovations—but execution of trades also requires private information. Second, sales are typically viewed as liquidity-driven and thus uninformative (Lakonishok and Lee, 2001; Dai et al., 2016). However, patent grant dates are exogenously set by the U.S. Patent and Trademark Office, unlike events such as earnings announcements or restatements that insiders can strategically manipulate (Ke, Huddart, and Petroni, 2003; Cheng and Lo, 2006; Rogers, 2008; Jagolinzer, 2009; Ravina and Sapienza, 2010). This institutional feature enables us to separate information-driven sales from those motivated by liquidity needs.

We posit that the link between competitor innovation and the profitability of insider sales can be reinforced in three ways. The first relates to product-market competition. When a rival firm introduces new innovations, the competitive pressure on peer firms intensifies. This heightened competition can erode the focal firm's market share, reduce pricing power, and compress future profit margins (Hou and Robinson, 2006; Tookes, 2008). In such an environment, corporate insiders—who possess a nuanced understanding of their firm's competitive positioning—may anticipate an adverse shift in expected firm value. This foresight can incentivize them to realize greater profits from stock sales before the market fully incorporates the negative implications of the competitor's innovation.

The second way concerns income risk. The wealth and compensation of top executives and other corporate insiders are often closely tied to firm performance, with a substantial portion of their remuneration linked to equity holdings or performance-based pay (Kallunki, Nilsson, and Hellström, 2009; Kallunki et al., 2018). Competitor innovation can heighten income risk for these individuals by reducing future firm performance and thus lowering both equity values and performance-based compensation. Kogan et al. (2021) show that earnings growth for workers—especially highly compensated executives such as CEOs—is sensitive to competitor innovation. Faced with elevated income risk, insiders may be motivated to engage in more profitable sales transactions as a means of hedging against anticipated declines in both firm value and personal income.

The third way involves long-term investment dynamics. Firms that lag behind technologically often respond to competitor innovation by cutting back on research and development (R&D) spending, particularly when constrained by limited internal funds or high external financing costs (Aghion et al., 2005; Aghion et al., 2010; Li, 2011). Such reductions in long-term investment can weaken the firm's future competitive position, further depressing its growth prospects and valuation. Insiders, aware of these strategic retrenchments, may foresee that the market will react negatively once the investment slowdown becomes apparent. Consequently, they can time their sales to benefit from current prices before the anticipated decline materializes.

Take together, these cross-sectional heterogeneities suggest that the profitability of insider sales as a hedge against competitor innovation should be particularly pronounced under certain conditions—namely, when the industry is highly competitive, when insiders face higher income risk, and when the firm reduces investment or operates under tighter financial constraints. We therefore formally state our second hypothesis:

**Hypothesis 2**. The profitability of sales transactions as a hedge against competitor innovation is significantly higher when a firm's industry is highly competitive, when insiders face higher income risk, and when firms reduce investments or face tighter financial constraints.

### 2.2 Insider silence and Follow-on innovation

Next, we examine whether insider sales undertaken as a hedge against competitor innovation can indirectly reveal the presence of follow-on innovators within left-behind firms. If insider sales reflect managers' recognition of heightened exposure to this negative externality, then firms whose insiders *do not* engage in such sales—that is, remain silent—are likely less severely affected by competitor innovation. This relative resilience could arise for two distinct, but not mutually exclusive, reasons.

First, the absence of insider selling may signal that managers perceive limited exposure to the adverse competitive impact, perhaps because their firms possess unique capabilities or complementary assets that mitigate the innovation shock. Second, insider silence may be a deliberate choice to avoid revealing proprietary information through trading behavior. Prior research suggests that insider transactions can convey valuable signals to the market and competitors; thus, refraining from trades may help protect sensitive strategic knowledge (Aboody and Lev 2000; Huddart and Ke 2007; Choi, Faurel, and Hillegeist, 2025). In this case, insider silence itself becomes a potential indicator that the firm holds valuable, non-public innovation-related information.

One potential concern is that insider purchases following competitor innovation could provide a stronger signal than insider silence, since purchases might reveal confidence to withstand negative externalities. The relative informativeness of purchases versus silence depends on proprietary costs: when these costs are sufficiently high, insiders refrain from trading and remain silent; when they are lower, insiders may choose to purchase. In untabulated analyses, we find that insider purchases do not convey proprietary information.

To empirically capture this dimension of proprietary information, we consider two complementary measures: the firm's subsequent patent filings, which capture codified innovative output, and its use of trade secrecy, which reflects tacit, non-codified knowledge protection. Taken together, these measures enable us to assess whether firms with silent insiders respond to competitor innovation not with a contraction in performance, but with sustained or increased innovative activity. This reasoning motivates our third hypothesis:

**Hypothesis 3**. Competitor innovation accompanied by insider silence does not reduce future sales growth, but instead increases subsequent patent filings and the use of trade secrecy.

Lastly, we explore the underlying economic mechanism. If insider silence reflects proprietary information, how is this information formed, and why does it manifest only through insider silence? We hypothesize that firms with insider silence transform competitor innovations into their own patents by learning from external knowledge. In other words, these firms benefit from knowledge spillovers. Such spillovers are particularly strong among technologically proximate firms (Jaffe, 1986; Bloom, Schankerman, and Van Reenen, 2013), suggesting that competitor innovation can be leveraged to create future opportunities.

Why do knowledge spillovers dominate negative externalities only for firms with insider silence? Both positive and negative externalities vary widely across firms (Bloom, Schankerman, and Van Reenen, 2013) and are difficult to observe directly. Insider trading behavior provides an indirect signal: insider silence implies that the net effect of knowledge spillover over displacement is beneficial, while sales suggest the opposite. Accordingly, we argue that follow-on innovators identified by insider silence build future patents on positive externalities from competitor innovation.

Turning to trade secrecy, knowledge spillovers play a distinct role. While trade secrecy also involves proprietary information, firms use it strategically to curb dissemination of knowledge (Glaeser, 2018; Chang, Tseng, and Yu, 2024). Thus, when proprietary information stems from knowledge spillovers, firms may rely less on secrecy and more on patents, since competitor innovations have already been disclosed. This leads to two complementary predictions: insider-silent firms increase patenting, while their reliance on trade secrecy diminishes.

**Hypothesis 4**. Competitor innovation accompanied by insider silence drives patent filings with knowledge spillovers, but it reduces trade secrecy.

## 3. Research design

In this section we describe the data, the measures of the negative externality of competitor innovation, and insider trading profitability. We also present the summary statistics and the design of the empirical specifications.

### 3.1 Data

We obtain an initial sample of insider transactions over the period running from 2003 through 2020 from the Thomson Financial Insiders Data Feed (IDF). We limit our sample to transactions executed in firms listed on the NYSE, the AMEX, or NASDAQ whose stock returns and financial data are available at the Center for Research in Security Prices (CRSP) and Compustat, respectively. We focus only on valid open market purchases and sales transactions of common shares without amendments.[9] We further require 1) share codes in CRSP to be 10 or 11, 2) traded prices to range between the daily low and high prices reported in CRSP, and 3) the number of trading shares to be lower than the total number of shares outstanding and total daily trading volume in CRSP. We also exclude regulated firms in the financial and utilities industries (with Standard Industry Classification (SIC) codes between 6000 and 6999 and between 4900 and

[9] A valid transaction is one without a cleanse code of “A” or “S.” Open market purchase and sales transactions have transaction codes of “P” or “S” but without an option sell indicator of “A” or “P”. Transactions with amendments are shown with an amendment indicator of “A” in the Thomson Financial IDF database.

4999). We obtain institutional ownership data from the Thomson Reuters institutional holdings (13F) database, board independence data from BoardEx, analyst forecasts data from I/B/E/S, and CEO compensation data from Compustat Execucomp. In our study, we focus mainly on sales transactions, so we drop purchase trades and winsorize all continuous variables at 1% and 99%. Also, we test how an insider trades to hedge against competitor innovation so we delete trades if an insider's firm issues a related patent. These restrictions result in a final sample of 639,891 sales transactions made by 4,252 unique firms and 30,107 unique insiders.

### 3.2 Variable definitions

#### 3.2.1 Competitor innovation

We use *innovation by competitors* as the measure of the negative externality of competitor innovation. Following Kogan et al. (2017), we estimate the market value of each patent $j$ ($\xi_j$) by calculating three-day announcement returns from t to t+2 when *t* is the issuance date.[10, 11] Kogan et al. (2017) document that the higher the market value of an innovation, the more future citations it receives. More importantly, Kogan at al. (2017) estimate competitor innovation value by aggregating innovation values by competitors, and show that such innovation adversely affects a focal firm's future output as evidence of a negative externality. Following Kogan et al. (2017), we estimate *innovation by competitors* as follows,

$$Innovation\ by\ competitors\ (\theta_{I/f}) = \frac{\sum_{f' \in I/f} \Theta_{f'}}{\sum_{f' \in I/f} B_{f'}}$$

[10] The USPTO issues patents every Tuesday unless there is a federal holiday.

[11] The authors provide details about the process involved in calculating the market value of each patent. The data are available on their website (https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data).

where *I/f* denotes firm *i*'s competitors, $\Theta_{f'}$ is the average market value of each patent *j* ($\xi_j$) for firm *i*'s competitors at time *t*, and $B_{f'}$ is the book value of assets of firm *i*'s competitors. Following Kogan et al. (2017), we define firm *i*'s competitors as firms that operate in the same SIC three-digit code industry, excluding firm *i*.

While Kogan et al. (2017) aggregate innovation value ($\Theta_{f'}$) and total assets ($B_{f'}$) across competitors for each year, we estimate *innovation by competitors* for each day as our insider transaction data indicates specific dates when transactions are executed. By matching the *innovation by competitors* to insider transaction data at daily frequency, we can exclude the liquidity motive for insider trading. Because the market value of a patent is estimated from the issuance date t to t+2, we match *innovation by competitors* to insider transactions on t+3.[12] We replace missing values with zeros. Lastly, we multiply *innovation of competitors* by 100.

### 3.2.2 Insider Trading Profitability

We measure insider trading profitability by estimating abnormal returns over the 180 calendar days that follow a transaction date. Specifically, the profitability of *innovation by competitors* is calculated from t+3 to t+183 where the issuance date is t. We choose a 180-day estimation period to be consistent with Rule 16(b) of the Securities Exchange Act of 1934 (namely, the short-swing rule), which requires all insiders to return profits earned from their trading during a given six-month period to their firms, which likely forces them not to reverse their positions within at least six months. Following Jagolinzer, Larcker, and Taylor (2011) and Ravina and Sapienza (2010), we use two measures of abnormal returns; *BHR* and *Carhart alpha*. *Carhart*

[12] Kogan et al. (2017) estimate innovation value by aggregating cumulative returns from the issuance date of each patent over a three-day period, showing that announcement returns reflect the future market value of innovations. Also, during that period, trading volume increases. We assume that insiders learn of innovation news regarding competitors by monitoring stock market reactions.

*alpha* is the intercept from the Carhart (1997) four-factor model estimated over the 180 calendar days following each trade, reported in percentages. *BHR* is calculated by subtracting compounded market returns using the CRSP value-weighted index from compounded returns to each firm over 180 calendar days following transaction dates. We require the number of trading days to be above 60. Because we focus on sales transactions, we multiply abnormal returns by -1, so a positive abnormal return represents the loss that insiders avoid by trading to hedge against competitor innovation.

### 3.3 Summary statistics

Table 1 presents the descriptive statistics for innovation, sales executed in response to competitor innovation, and transaction characteristics. The appendix provides detailed description of the variables. Panel A provides the summary statistics for innovation characteristics. The mean of *innovation by competitors* is 0.155 with a standard deviation of 0.106. Total number for of *innovation by competitors* is 7,317. Next, we count the number of competitors who announce innovations on the same issuance date. On average, about 10.80 competitors announce innovations on the same date through the USPTO. This finding tells us that only a few competitors are successfully granted innovation patents and actually benefit from an innovation. This could be a threat to the remaining firms that do not engage in innovation. Turning to Panel B, the data reported enable us to compare sales driven by competitor innovation with other sales. Trade size and shares are smaller for sales transactions driven by competitor innovation than for other sales transactions, but previous ownership is higher for sales transactions that hedge against competitor innovation. Lastly, Panels C shows transaction characteristics.

Table A.1 presents the distribution of sales transactions executed to hedge against competitor innovation in each year across industries. During our sample period, 8 percent of all insider sales occur after competitors announce innovations. The number of sales transactions executed to hedge against competitor innovation is highest in 2007 (9,828 trades), followed by 2008 (7,468) and 2006 (6,316). After the Great Recession, the number of sales transactions fell below 3,000. Across industries, sales transactions were executed mainly in manufacturing industries (60%), followed by service industries (34%). Overall, Table A.1 shows that sales transactions driven by competitor innovation were executed widely over time and across industries.

### 3.4 Empirical design

To testify the effect of the negative externality of competitor innovation on insider trading profitability (Hypothesis 1), we specify a regression model at firm-insider-transaction level as follows:

$$Profitability = \alpha + \beta_{I/f}\theta_{I/f} + \beta_{\vec{X}}\vec{X} + \beta_{FE}Fixed\ effects + \varepsilon. \qquad (1)$$

Profitability can be measured as either *Carhart alpha* or *BHR* for each transaction. The main variable is *innovation by competitors* ($\theta_{I/f}$). We expect the coefficient of $\theta_{I/f}$, $\beta_{\theta}$, to be significantly positive for insider sales, suggesting that the profitability of the insider sales is significantly higher when competitors create highly valuable innovations.

$\vec{X}$ is a vector of control variables. Following Lakonishok and Lee (2001), we include firm size (*Log (firm size)*), the market-to-book ratio (*MB*), and *past returns* because these variables are important return determinants (e.g., Fama and French, 1993; Jegadeesh and Titman, 1993). We control for *ROA* because a firm's profitability is an important determinant of insider transactions (Ke, Huddart, and Petroni, 2003). Further, we include investment (*Investment/total asset*), R&D intensity (*R&D/sale*), *stock return volatility*, *analyst dispersion*, and *institutional ownership* to capture the effects of information asymmetry and investment opportunities on insider trading profitability (Aboody and Lev, 2000; Huddart and Ke, 2007). *Board independence* controls for the effect of firm governance (Dai et al., 2016). *Equity ownership by each insider* and *transaction size* are controlled for the behavior of insiders. We include *blackout period* (an indicator that equals one if insiders trade during the blackout period and zero otherwise) because it curbs insider transactions (Bettis, Coles, and Lemmon, 2000). Lastly, we add firm and year fixed effects to control for unobserved cross-sectional and time-series variations, and cluster standard errors at the firm level.

Next, to examine the economic channel for Hypothesis 2, we rely on the subsample analysis with model (1). For the product-market competition channel, we divide insider transactions based on the median value of *HHI* (Robinson and Hou, 2006). We expect the coefficient of $\theta_{I/f}$ to be more significantly positive when *HHI* is low.

For the insider income risk channel, we match transaction data to CEO compensation data and conduct subsample tests on the median of either total compensation or incentive pay. We use the natural logarithm of total compensation (*log(Total compensation)*) to capture income risk for individuals. We hypothesize that the coefficient of $\theta_{I/f}$ is significantly positive when *log(Total compensation)* is large.

To measure long-term investments, we use *R&D intensity*. To measure financial constraints, we use *Leverage*. We conjecture that the coefficient of $\theta_{I/f}$ is significantly positive when *R&D intensity* is low and when *Leverage* is high.

Following Suh (2023), to address endogeneity concerns we compare the profitability of insider trading to hedge against competitor innovation before and after competitors are affected directly by the 2008 FC ruling. Property rights associated with a patent between employees and their firms are arranged by pre-invention assignment agreements in employment contracts. From the late 1970s to the early 1980s, eight states, including California, Delaware, Illinois, Kansas, Minnesota, North Carolina, Utah, and Washington, enacted statewide legislation to protect employees from employer abuse of superior negotiation power over employee inventions. In 2008, the Federal Circuit handed down a decision,[13] which shifted property rights from employees to firms, favoring firms in invention-assignment agreements in those eight states. Suh (2023) uses the 2008 FC ruling as an exogenous shock and finds that firms headquartered in any of those eight states increased credits and innovation activities (e.g., patents) after the 2008 FC ruling.

Inasmuch as the exogenous shock of the 2008 FC ruling affected competitor innovation, we estimate the treatment index (*Treatment index*) in two steps. First, for each focal firm we identify competitors' headquarters for which patents are issued using 10-X Header data (Loughran and McDonald, 2016).[14, 15] Second, we create an indicator that equals 1 if a competitor is located in one of the eight states and 0 otherwise. We then estimate the book-value weighted average of the indicator for each focal firm. The higher is the value of *Treatment index* for a focal firm the more competitor innovation is observed in the eight states. Empirically, we estimate the following regression:

$$Profitability = \alpha + \beta_{I/f}\theta_{I/f} + \beta_{TI}Treatment\ index\ (TI) + \beta_{Post}Post3years + \beta_{Pre}Pre3years + \beta_{I/f*TI}\theta_{I/f} * TI + \beta_{Post*I/f}Post3years * \theta_{I/f} + \beta_{Pre*I/f}Pre3years * \theta_{I/f} + \beta_{Post*TI}Post3years * TI + \beta_{Pre*TI}Pre3years * TI + \beta_{Post*I/f*TI}Post3years * \theta_{I/f} * TI + \beta_{Pre*I/f*TI}Pre3years * \theta_{I/f} * TI + \beta_{\vec{X}}\vec{X} + \beta_{FE}Fixed\ effects + \varepsilon. \quad (2)$$

[13] *DDB Technologies LLC v. MLB Advanced Media, LLP*.

[14] https://sraf.nd.edu/sec-edgar-data/10-x-header-data/

[15] We use 10-X Header data because doing so allows us to obtain historical headquarters information. Based on data availability, the final sample period ends in 2018.

To leverage the exogenous 2008 shock, we use two indicator variables, *Post3years* and *Pre3years*. *Post3years* (*Pre3years*) equals 1 if a transaction is executed 2 years after and on (3 years before) 2008.[16] For the robustness, we estimate the parallel trend over 3 years following the 2008 FC ruling as well. We expect the post-shock triple interaction term, $\beta_{Post*I/f*TI}$, to be significantly positive.

To examine whether competitor innovation accompanied by insider silence reveals follow-on innovation (Hypothesis 3), we aggregate competitor innovation at the firm-year level and decompose it into competitor innovation accompanied by insider silence ($\theta_{I/f}^{Silence}$) and competitor innovation accompanied by insider sales ($\theta_{I/f}^{Sales}$). The regression is as follows:

$$Y = \alpha + \beta_{\theta}\theta_i + \beta_{\theta_{I/f}^{Silence}}\theta_{I/f}^{Silence} + \beta_{\theta_{I/f}^{Sales}}\theta_{I/f}^{Sales} + \beta_{\vec{X}}\vec{X} + \beta_{FE}Fixed\ effects + \varepsilon. \quad (3)$$

Consistent with Kogan et al. (2017), we estimate and control for the innovation value of focal firm $i$ ($\theta_i$). We also include size, the book-to-market ratio, past returns, idiosyncratic volatility, leverage, ROA, R&D expenditures, a loss indicator, an R&D indicator, and institutional ownership, as in Glaeser (2018). To examine whether competitor innovation results in a negative externality, we use next year's sales growth (*Sales growth*) as a dependent variable (Y). We expect $\beta_{\theta_{I/f}^{Sales}}$ to be significantly negative while $\beta_{\theta_{I/f}^{Silence}}$ should be insignificant. Further, we use the number of patents (*patent filing*) and trade secrecy as dependent variables (Y) to test whether insider silence reveals follow-on innovation and whether insider sales predict proprietary information, respectively. We expect $\beta_{\theta_{I/f}^{Sales}}$ to be insignificant while $\beta_{\theta_{I/f}^{Silence}}$ should be significantly positive. With *Sales growth* and *Patent filing* we use firm and year fixed effects. For

[16] We use the full sample period from 2003 through 2018 but the results are quantitatively similar when we reduce our sample period to a five-year window (2003 through 2013) or a three-year window (2005 through 2011).

*Trade secrecy* we estimate a probit regression with industry and year fixed effects. Standard errors are estimated at the firm level.

Last, we explore the economic mechanism (Hypothesis 4). We estimate knowledge spillovers (*Spillover*) following Jaffe (1987), and Bloom, Schankerman, and Van Reenen (2013), relying on patent classes. We then interact *Spillover* with $\theta_{I/f}^{Silence}$ and $\theta_{I/f}^{Sales}$, respectively.:

$$Patent\ filing\ or\ Trade\ secrecy = \alpha + \beta_{\theta}\theta_i + \beta_{\theta_{I/f}^{Silence} * Spillover}\theta_{I/f}^{Silence} * Spillover + \beta_{\theta_{I/f}^{Sales} * Spillover}\theta_{I/f}^{Sales} * Spillover + \beta_{\theta_{I/f}^{Silence}}\theta_{I/f}^{Silence} + \beta_{\theta_{I/f}^{Sales}}\theta_{I/f}^{Sales} + \beta_{Spillover} * Spillover + \beta_{\vec{X}}\vec{X} + \beta_{FE}Fixed\ effects + \varepsilon. \quad (4)$$

We test whether $\beta_{\theta_{I/f}^{Silence} * Spillover}$ is significantly positive on *Patent filing* while $\beta_{\theta_{I/f}^{Sales} * Spillover}$ is insignificant. Turning to *Trade secrecy*, we expect $\beta_{\theta_{I/f}^{Silence} * Spillover}$ to be significantly negative while $\beta_{\theta_{I/f}^{Silence}}$ should be significantly positive.

## 4. Main Results: Insider Trading Profitability

### 4.1 Baseline findings

Columns (1) and (2) of Table 2 present the regression results for insider trading profitability when hedging against *innovation by competitors* ($\theta_{I/f}$) in insider sales. As seen in column (1), we find that the coefficient on *innovation by competitors* is positive and significant at the 5% level. The coefficient of 0.048 for *innovation by competitors* suggests that a one-standard-deviation increase in this variable is associated with a 0.92% increase in *Carhart alpha* over 180 days. For column (2) we replace *Carhart alpha* with *BHR*. As is the case with *Carhart alpha*, the effect and the magnitude of *innovation by competitors* are significantly positive at the 1% significance level. Overall, when the USPTO issues patents to a focal firm's competitors, insiders in the focal firm sell their shares and earn significant profits. This is consistent with Hypothesis 1, according to which insiders engage in the sales transactions to hedge against the negative externality of competitor innovation.

Turning to columns (3) and (4), we focus on purchase transactions. If *innovation by competitors* on average generates a positive externality, we should find abnormal profits, but we do not find significant profits from purchase transactions. This suggests that the purchase transactions don't react to competitor innovation. Also, this echoes findings reported in Bloom, Schankerman, and Van Reenen (2013), who show that a negative externality exists in the same product-market space.[17]

**4.2 Cross-sectional tests**

In this subsection we do cross-sectional tests through which insiders earn abnormal profits from sales when hedging against competitor innovation. First, we divide our sample using the median value of *HHI* and estimate equation (1) for each subsample, reporting the results in Panel A of Table 3. As seen in columns (1) and (2), we find that the coefficient of *Carhart alpha* is positive and significant at the 5% level for the subsample with lower *HHI* while the coefficient is insignificant for the subsample with higher *HHI*. We replace *Carhart alpha* with *BHR* for columns (3), and (4) and find similar results.

To further investigate the effect of product-market competition, we divide competitors into local and non-local competitors. As multiple competitors issue innovations at the same time, we measure the average distance between innovative competitors and a focal firm. We then define *innovation by local (non-local) competitors* based on whether the average distance is below (above)

[17] Bloom, Schankerman, and Van Reenen (2013) provide empirical measures for knowledge spillover (positive externality) and business stealing (negative externality), respectively. They estimate the weighted average of R&D capital among technologically-related peers (industry peers) to measure positive externality (negative externality).

the median. We calculate distance by using either kilometers (km) or a same-state dummy variable, which equals 1 if a focal firm and a competitor are located in the same state and zero otherwise.[18] The results are shown in Table A.3 of the appendix. We find that all coefficients of *innovation by local competitors* are positive and significant while these of *innovation by non-local competitors* are insignificant except in column (4).

Second, to examine the effect of income risk, we divide our sample according to the sample median of *Log(total compensation)*. In Panel B, the coefficients of both *Carhart alpha* and *BHR* are significantly positive for the subsample with high *Log(total compensation)*, as reported in columns (1) and (3) while they are insignificant for the subsample with low *Log(total compensation)*, as reported in columns (2) and (4).

Third, we divide our sample into two subsamples based on either *R&D intensity* or *Leverage*, and report the results in Panels C and D, respectively. In columns (1) and (2), the coefficient of *innovation by competitors* is significantly positive when *R&D intensity* is below the median value. We use *BHR* for columns (3) and (4) and obtain similar results. In Panel D, we see in columns (1) and (3) that the coefficients of *innovation by competitors* are significantly positive when *leverage* is above the median value, but we see in columns (2) and (4) that the coefficients of *innovation by competitor* are insignificant.

Overall, the results reported in Table 3 confirm that insiders earn abnormal sales profits when hedging against the negative externality of competitor innovation if product-market competition is intense, if insider income risk is high, and if insiders' firms have lower investment.

### 4.3 Addressing endogeneity

[18] Inasmuch as we take the average value of the same-state dummy, the interpretation should be based on how many competitors are located in the same state among all innovating competitors.

We present regression results obtained using the 2008 FC ruling as an exogenous shock in Table 4. To save space, we show results only for the main interaction terms.[19] In columns (1) and (2), we find that the coefficient of the triple interaction term between *innovation by competitors*, the treatment index, and post-3 years ($\beta_{Post*I/f*TI}$) is significantly positive while the coefficient of the triple interaction term between *innovation by competitors*, the treatment index, and pre-3 years ($\beta_{Pre*I/f*TI}$) is insignificant. These findings indicate that, after the 2008 FC ruling passed, insiders earned the significant profits when hedging against innovation by competitors whose headquarters are located in one of the eight states. For columns (3) and (4), we estimate parallel trends and find that insiders enjoy high profitability when their competitors are headquartered in one of the eight states 1 and 3 years after the 2008 FC ruling.

**4.4 Robustness checks**

In this subsection we present the results of robustness tests obtained after changing the specification of *innovation by competitors* with respect to transaction timing, the definition of competitors, and aggregating multiple transactions.

We match insider transactions executed 3 days after the USTPO issues patents to competitor innovations because Kogan et al. (2017) estimate innovation value based on the announcement returns from a patent's issuance date to 2 days after the issuance date. We change the time gap between insider transactions and issuance dates of competitor innovations. First, we match transactions executed 1 day before issuance dates to competitor innovations. If an insider knows about competitor innovations before it is publicly announced by the USPTO, we expect to observe significantly positive trading profits for insiders, but instead we see that the coefficient of *innovation by competitors* is insignificant in columns (1) and (2) of Panel A of Table 5. This

[19] The full version of Table 7 is available upon request.

finding tells us that insiders do not know about competitor innovations before the USPTO issues the corresponding patents. Rather, insiders monitor the threat of innovation via the stock market after competitor innovations are issued. For columns (3) and (4) ((5) and (6)), we extend the time gap from 3 days to 7 days (14 days) after issuance dates by assuming that insiders need longer time to process competitor innovation threat. We show results similar to those reported in Table 2.

Second, we change the definition of competitors by replacing the SIC 3-digit classification to the Text-based Network Industry Classification (TNIC) in Hoberg and Philips (2016). Results reported in columns (1) and (2) of Panel B show that insiders enjoy positive profitability when the definition of competitors changes. We further decompose competitors based on product fluidity or product similarity. Product fluidity captures competitive threats posed by product offerings (Hoberg, Philips, and Prabhala, 2014) and product similarity captures the degree of similarity between two firms' products (Hoberg and Philips, 2016). Based on the median value of competitor fluidity or similarity for each focal firm, we divide *innovation by competitors* into *innovation by competitors (High)* and *innovation by competitors (Low)*. As seen in columns (3) and (4), we find that insiders enjoy significant profitability when competitors with new patents face greater market threats (fluidity). In columns (5) and (6), the results we report show that insiders enjoy positive profits when competitors' products are similar.

Third, we aggregate insider transactions at either the firm-insider-transaction-date level or the firm-transaction-date level to address bias caused by cross-sectional dependence when multiple insiders in the same firm trade simultaneously multiple times. We aggregate both purchase and sales transactions on each firm-insider-transaction date (or firm-transaction date), and retain observations if the number of sales transactions is higher than the number of purchase transactions. As seen in Panel C, we still find that insiders earn significantly positive profits when hedging against competitor innovation.

## 5. Identifying follow-on innovators based on insider sales

### 5.1 Effect of competitor innovation: Insider sales vs. Insider silence

So far, we have shown that insiders exploit the opportunity to earn insider profits to avoid the negative externality of competitor innovation. On the other hand, given that insider trading is restricted to curb the dissemination of the proprietary information (Choi, Faurel, and Hillegeist, 2025), we expect firms whose insiders do not trade their shares to hedge against competitor innovation to hold proprietary information that they use to inform follow-on innovation. We estimate model (3) and report the results in Table 6.

First, we examine whether a negative externality based on competitor innovation exists using future sales growth for column (1). We find that $\theta_{I/f}^{Sales}$ is significantly negative while $\theta_{I/f}^{Silence}$ is insignificant. Firms in which insiders sell their shares to avoid the negative externality of competitor innovation will experience lower sales growth, but firms in which insiders remain silent against competitor innovation are not exposed. This echoes the finding of Kogan, Papanikolaou, and Stoffman (2020), who find that exposure to negative externalities is heterogeneous across firms.

Second, we investigate why firms marked by insider silence experience less damage from competitor innovation. If a silent insider possesses proprietary information about follow-on innovation, it will obtain a higher number of patents or maintain trade secrecy. In column (2), the coefficient of $\theta_{I/f}^{Silence}$ is significantly positive on *Patent filing* at the 5% significance level while $\theta_{I/f}^{Sales}$ is insignificant. Untabulated result shows that the insider purchase following competitor innovation does not predict *Patent filing*, suggesting that the insider silence possess the proprietary information.[20] As seen in column (3), we find similar results for *Trade secrecy*. $\theta_{I/f}^{Silence}$ is significantly positive at the 1% significance level while $\theta_{I/f}^{Sales}$ is only marginally positive. Overall, these results are consistent with Hypothesis 3. That said, even though firms operating in the same product market experience the negative externality of competitor innovation, they respond heterogeneously. Insider silence helps us identify firms that create follow-on innovations in left-behind firms.

**5.2 Follow-on innovation: Knowledge-spillover channel**

We explore the economic channel for follow-on innovation in firms marked by insider silence and report the results in Table 7. Higher innovation value means higher quality, resulting in higher-quality follow-on innovation via knowledge dissemination, but not all firms enjoy this positive externality. The literature finds that knowledge spillovers exist if peers share technology spaces such as patent classes (Jaffe, 1986; Bloom, Schankerman, and Van Reenen, 2013). We conjecture that rival followers are less severely damaged by the negative externality of competitor innovation and engage in follow-on innovation via knowledge spillovers.

First, results reported in column (1) of Table 7 indicate that *competitor innovation* ($\theta_{I/f}$) increases future *Patent filing* through knowledge spillovers. While *competitor innovation* is insignificant, the interaction term between *competitor innovation* and *Spillove*r is significantly positive. For column (2), we decompose *competitor innovation* into *competitor innovation accompanied by insider silence* ($\theta_{I/f}^{Silence}$) and *competitor innovation accompanied by insider sales*

[20] In the same manner, we estimate the regression using the insider purchase. The coefficient of competitor innovation followed by the insider purchase ($\theta_{I/f}^{Purchase}$) is 0.29 with t-statistics of 0.54. The detailed regression results are available upon request.

($\theta_{I/f}^{Sales}$), and estimate model (4). The interaction term between $\theta_{I/f}^{Silence}$ and *Spillover* is significantly positive. This clearly shows that proprietary information is based on a positive externality generated by competitor innovation.

Second, we use *Trade secrecy* for columns (3) and (4) of Table 7. We find that *competitor innovation* is significantly positive on *Trade secrecy*, especially when accompanied by insider silence. Without knowledge spillover, competitor innovation accompanied by insider silence still increases the trade secrecy. More interestingly, we find that the interaction term between *competitor innovation* and knowledge spillovers is significantly negative. This finding suggests that follow-on innovators who rely on knowledge spillovers depend to a lesser extent on trade secrecy, thereby expediting knowledge dissemination.

**5.3 Cross-sectional analysis**

We conduct two cross-sectional analyses. First, the negative externality of competitor innovation is stronger in a competitive product market, spurring insider sales. That said, our identification of insider sales becomes stronger in a competitive product market. We divide the sample based on the median value of *Lerner index* and estimate models (3) and (4), reporting the results in Table 8. We use *Patent filing* as the dependent variable. As seen in columns (1) and (2), we find that $\theta_{I/f}^{Silence}$ is positively significant only in a competitive product market. Also, the interaction term between $\theta_{I/f}^{Silence}$ (*competitor innovation* ($\theta_{I/f}$)) and *Spillover* is significant only in a competitive product market, as seen in column (6) (column (4)).

Second, our identification assumes that firms respond heterogeneously to the negative externality of competitor innovation. Kogan, Papanikolaou, and Stoffman (2020) find that growth firms are less severely affected by competitor innovation than value firms. We examine whether our identification strategy helps to explain the heterogeneity between growth and value firms. We estimate models (3) and (4) after we divide the sample based on the median value of the market-to-book ratio (*MB*) and report the results in Table 9. As seen in columns (1) and (2), we find that the interaction term between *competitor innovation* ($\theta_{I/f}$) and *Spillover* is significantly positive only for growth firms. Further, in columns (3) and (4), we use $\theta_{I/f}^{Silence}$ and $\theta_{I/f}^{Sales}$ and find that $\theta_{I/f}^{Silence}$ increases *Patent filing* via knowledge spillovers for growth firms. $\theta_{I/f}^{Silence}$ does not predict follow-on innovation for value firms. These results tell us that growth firms hedge against the negative externality of competitor innovation by leveraging it into a positive externality.

## 6. Conclusion

In this study we identify which firms transform competitor innovations into follow-on innovation and which fail to adapt using insider sales executed to hedge against competitor innovation. First, we find abnormal profits from insider sales to hedge against competitor innovation, with the economic channels relying on product competition, insiders' income risk, and long-term investment. These findings are robust to the use of the 2008 Federal Circuit ruling as an exogenous shock as well as to various specifications obtained by changing the transaction timing and the definition of competitors as well as when aggregating multiple transactions. Indeed, insider sales reflect the extent to which firms are exposed to the negative externality of competitor innovation and fear being displaced.

Second, we distinguish firms that are exposed to the negative externality of competitor innovation into follow-on innovators in left-behind firms depending on whether insiders in focal firms are silent or execute sales transactions to hedge against competitor innovation. We find that competitor innovation inhibits sales growth for firms in which insiders sell their shares to avoid the negative externality of competitor innovation, while firms in which insiders are silence increase future patents and trade secrecy. They are less severely affected by competitor innovation because their follow-on patents are based on knowledge spillovers.

Overall, our findings shed light on how insiders react to the negative externality of competitor innovation and show how some firms survive the negative externality via a positive externality, knowledge spillovers.

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**TABLE 1**
**Summary statistics**

Panel A: Innovation characteristics

| | Mean | STD | P10 | P25 | Median | P75 | P90 | N |
|---|---|---|---|---|---|---|---|---|
| Innovation by competitors | 0.155 | 0.106 | 0.031 | 0.068 | 0.130 | 0.229 | 0.339 | 7,317 |
| The number of competitors announcing the Innovation in the same date | 10.795 | 11.228 | 1 | 1 | 5 | 18 | 29 | 7,317 |

Panel B: Sales characteristics depending on competitor innovation

| | Sales driven by competitor innovation | | | | Other sales | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Mean | STD | Median | N | Mean | STD | Median |
| Unique insiders | | | | | | | | |
| Trade shares/insider (#mil) | 6,621 | 0.046 | 0.140 | 0.010 | 23,486 | 0.159 | 1.900 | 0.020 |
| Trade size/insider ($mil) | 6,621 | 1.406 | 5.448 | 0.282 | 23,486 | 5.745 | 66.619 | 0.693 |
| Previous ownership (%) | 6,621 | 1.576 | 4.487 | 0.111 | 23,486 | 0.906 | 3.309 | 0.057 |
| Unique firms | | | | | | | | |
| Size | 1,621 | 6.578 | 1.550 | 6.438 | 2,631 | 6.668 | 1.592 | 6.520 |
| MB | 1,621 | 3.802 | 4.194 | 2.659 | 2,631 | 3.553 | 3.805 | 2.508 |

Panel C: Transaction characteristics

| Variables | Mean | STD | P10 | P25 | Median | P75 | P90 | N |
|---|---|---|---|---|---|---|---|---|
| Carhart alpha (%) | 0.000 | 0.190 | -0.226 | -0.102 | 0.003 | 0.111 | 0.226 | 631,891 |
| Buy and hold return | 0.986 | 0.244 | 0.710 | 0.857 | 0.986 | 1.130 | 1.289 | 631,891 |
| Innovation by competitors | 0.014 | 0.053 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 631,891 |
| Firm size | 1188.610 | 5.504 | 149.844 | 306.055 | 922.239 | 3832.360 | 14357.001 | 631,891 |
| MB | 4.634 | 5.203 | 1.210 | 1.891 | 3.132 | 5.070 | 8.879 | 631,891 |
| ROA | 0.061 | 0.091 | -0.026 | 0.028 | 0.065 | 0.109 | 0.156 | 631,891 |
| Investment/total asset | 0.048 | 0.048 | 0.010 | 0.017 | 0.034 | 0.057 | 0.105 | 631,891 |
| R&D/Sales | 0.067 | 0.104 | 0.000 | 0.000 | 0.011 | 0.109 | 0.199 | 631,891 |
| Stock return volatility | 0.027 | 0.011 | 0.014 | 0.019 | 0.025 | 0.033 | 0.042 | 631,891 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Analyst dispersion | 0.102 | 0.268 | 0.004 | 0.008 | 0.021 | 0.061 | 0.231 | 631,891 |
| Institutional ownership | 0.734 | 0.207 | 0.422 | 0.607 | 0.762 | 0.884 | 0.971 | 631,891 |
| Board independence | 0.804 | 0.100 | 0.667 | 0.750 | 0.833 | 0.875 | 0.900 | 631,891 |
| Equity ownership by each trader | 0.050 | 0.078 | 0.000 | 0.001 | 0.008 | 0.079 | 0.154 | 631,891 |
| Transaction size | 0.001 | 0.002 | 0.000 | 0.000 | 0.000 | 0.001 | 0.003 | 631,891 |
| Blackout period | 0.540 | 0.498 | 0.000 | 0.000 | 1.000 | 1.000 | 1.000 | 631,891 |
| Past return | 1.145 | 0.294 | 0.851 | 0.957 | 1.091 | 1.262 | 1.523 | 631,891 |

Panel A of this table summarizes competitors' innovation value and the number of competitors announcing innovations on the same date, including the mean (Mean), standard deviation (STD), percentiles, and observations (N). The innovation by competitors is the ratio of the sum of the market value of competitor innovations over the sum of the competitors' total assets. The market value of innovations is estimated in Kogan et al. (2017) and we download data from the authors' website. Panel B presents descriptive statistics for transaction characteristics at either the insider level or the firm level between sales transactions driven by competitor innovations and by others. Panels C show descriptive statistics for transaction characteristics. The sample period runs from 2003 through 2020.

**TABLE 2**
**Trading profitability and Innovation by competitors**

| | Sales | | Purchases | |
|---|---|---|---|---|
| | Carhart alpha | Buy and hold return (BHR) | Carhart alpha | Buy and hold return (BHR) |
| Independent variable | (1) | (2) | (3) | (4) |
| Innovation by competitors | 0.048** | 0.088*** | -0.005 | 0.007 |
| | (0.018) | (0.003) | (0.884) | (0.864) |
| Log (firm size) | 0.076*** | 0.088*** | -0.128*** | -0.161*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| MB | 0.002 | 0.004*** | -0.007** | -0.009** |
| | (0.228) | (0.008) | (0.029) | (0.049) |
| ROA | 0.095 | 0.197** | -0.457*** | -0.619*** |
| | (0.134) | (0.013) | (0.002) | (0.000) |
| Investment/total asset | 0.420*** | 0.350* | -0.251 | -0.277 |
| | (0.006) | (0.095) | (0.284) | (0.397) |
| R&D/Sales | -0.122 | -0.109 | -0.001 | 0.012 |
| | (0.209) | (0.433) | (0.969) | (0.743) |
| Stock return volatility | 0.498 | 0.952 | 1.737 | 3.718** |
| | (0.441) | (0.315) | (0.200) | (0.042) |
| Analyst dispersion | -0.027*** | -0.022 | -0.012 | -0.019 |
| | (0.007) | (0.135) | (0.602) | (0.547) |
| Institutional ownership | 0.140** | 0.250*** | 0.148 | 0.182 |
| | (0.022) | (0.004) | (0.357) | (0.441) |
| Board independence | 0.012 | 0.010 | 0.093 | 0.203 |
| | (0.786) | (0.878) | (0.394) | (0.195) |
| Equity ownership by each trader | 0.043 | 0.103 | -0.518* | -0.655* |
| | (0.534) | (0.314) | (0.069) | (0.096) |
| Transaction size | -2.790 | -6.336** | 8.975** | 7.618** |
| | (0.129) | (0.019) | (0.011) | (0.024) |
| Blackout period | -0.003 | -0.009 | -0.008 | 0.010 |
| | (0.458) | (0.120) | (0.309) | (0.355) |
| Past return | 0.084*** | 0.130*** | -0.257*** | -0.364*** |
| | (0.000) | (0.000) | (0.003) | (0.000) |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.293 | 0.292 | 0.476 | 0.496 |
| Observations | 631,891 | 631,891 | 109,414 | 109,414 |

This table presents estimates obtained from ordinary least square (OLS) regressions of trading profitability on the innovation value of competitors. The sample consists of 631,891 insider sales and 109,414 insider purchases from 2003 through 2020. The dependent variable for columns (1) and (3) is the Carhart alpha from Carhart (1997) four-factor models estimated over 180 days following transaction dates (*Carhart alpha*), reported in percentages, and the dependent variable for columns (2) and (4) is market-adjusted buy-and-hold returns over the 180 days following transaction dates (*Buy and hold return* (*BHR*)). For sales transactions, abnormal returns are multiplied by -1. *Innovation by competitors* is the ratio of the sum of the market value of competitor innovations over the sum of competitors' total assets two days before transaction dates. We define competitors as firms whose industry code (SIC 3-digit) is the same as the focal firm's. The appendix provides detailed definitions of the variables. *P*-values reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**TABLE 3: Cross-sectional tests**

| Panel A. Product market competition | Herfindal-Hershman Index (HHI) | | | |
|---|---|---|---|---|
| | Carhart alpha | | BHR | |
| | High | Low | High | Low |
| Independent variable | (1) | (2) | (3) | (4) |
| Innovation by competitors | 0.029 | 0.056** | 0.075* | 0.092** |
| | (0.322) | (0.037) | (0.058) | (0.023) |
| Controls (same as Table 3) | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.303 | 0.316 | 0.293 | 0.316 |
| Observations | 316,672 | 315,199 | 316,672 | 315,199 |
| Panel B. Income risk | Log (Total Compensation) | | | |
| Innovation by competitors | 0.088* | -0.017 | 0.175** | -0.016 |
| | (0.062) | (0.508) | (0.018) | (0.583) |
| Controls (same as Table 3) | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.297 | 0.319 | 0.291 | 0.373 |
| Observations | 193,895 | 193,225 | 193,895 | 193,225 |
| Panel C. Long-term investment | R&D intensity | | | |
| Innovation by competitors | 0.037 | 0.065** | 0.057 | 0.135*** |
| | (0.157) | (0.046) | (0.144) | (0.000) |
| Controls (same as Table 3) | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.326 | 0.309 | 0.313 | 0.317 |
| Observations | 315,989 | 315,888 | 315,989 | 315,888 |
| Panel D. Financial constraint | Leverage | | | |
| Innovation by competitors | 0.061* | 0.027 | 0.098*** | 0.067 |
| | (0.056) | (0.293) | (0.009) | (0.103) |
| Controls (same as Table 3) | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.362 | 0.315 | 0.350 | 0.326 |
| Observations | 319,840 | 311,990 | 319,840 | 311,990 |

This table presents estimates obtained from ordinary least square (OLS) regressions of trading profitability depending on three channels: the product-market competition channel, the income-risk channel, and the investment channel. The sample consists of 631,871 insider sales executed from 2003 through 2020. The dependent variable for columns (1) and (2) is *Carhart alpha* and the dependent variable for columns (3) and (4) is *BHR*. The sample is divided into two subgroups according to the median of either *Herfindal-Hershman Index* for Panel A (*Log(CEO total compensation)* for Panel B, R&D intensity in the focal firm for Panel C, and *Leverage* for Panel D). *Herfindal-Hershman Index* is the 3-year average of the sum of squared market shares using total sales in each industry and each year. *Log(CEO total compensation)* is the natural logarithm of CEO total compensation. *R&D intensity* is the ratio of R&D expenditures to sales. *Leverage* is the ratio of total liabilities to total assets. The appendix provides detailed definitions of the variables. *P*-values reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 4**
**Trading profitability and Innovation by competitors: Exogenous shock**

| | Post 3 years | | Post 1, 2, 3 years | |
|---|---|---|---|---|
| | Carhart alpha | BHR | Carhart | BHR |
| Independent variable | (1) | (2) | (3) | (4) |
| Innovation by competitors (a) | 0.037 | 0.056 | 0.038 | 0.057 |
| | (0.327) | (0.312) | (0.308) | (0.296) |
| Treatment index (b) | -0.011 | -0.012 | -0.012 | -0.013 |
| | (0.190) | (0.246) | (0.182) | (0.238) |
| (a)* (b) | -0.021 | -0.040 | -0.023 | -0.043 |
| | (0.779) | (0.689) | (0.763) | (0.665) |
| Post 3 years*(a)* (b) | 0.639*** | 0.536* | | |
| | (0.006) | (0.078) | | |
| Pre 3 years*(a)* (b) | 0.045 | 0.202 | | |
| | (0.788) | (0.378) | | |
| Post_3*(a)* (b) | | | 0.631* | 0.723* |
| | | | (0.066) | (0.083) |
| Post_2*(a)* (b) | | | 0.395 | 0.328 |
| | | | (0.147) | (0.318) |
| Post_1*(a)* (b) | | | 0.987** | 0.414 |
| | | | (0.013) | (0.399) |
| Pre_1*(a)* (b) | | | 0.083 | 0.232 |
| | | | (0.754) | (0.551) |
| Pre_2*(a)* (b) | | | -0.026 | 0.121 |
| | | | (0.899) | (0.672) |
| Pre_3*(a)* (b) | | | 0.076 | 0.194 |
| | | | (0.778) | (0.528) |
| Pre 3 years, Post 3 years | Yes | Yes | No | No |
| Interaction between (a), (b), and Pre 3 years, Post 3 years | Yes | Yes | No | No |
| Pre_1, Pre_2, Pre_3, Post_1, Post_2, Post_3 | No | No | Yes | Yes |
| Interaction between (a), (b), and Pre_1, Pre_2, Pre_3 | No | No | Yes | Yes |
| Interaction between (a), (b), and Post_1, Post_2, Post_3 | No | No | Yes | Yes |
| Controls (same as Table 3) | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.301 | 0.301 | 0.303 | 0.304 |
| Observations | 616,599 | 616,599 | 616,599 | 616,599 |

This table presents estimates obtained from ordinary least square (OLS) regressions of trading profitability using an exogenous shock. The sample consists of 616,599 insider sales executed from 2003 through 2018. The dependent variable for columns (1) and (3) is the Carhart alpha from the Carhart (1997) four-factor models estimated over 180 days following transaction dates (*Carhart alpha*), reported in percentages, and the dependent variable for columns (2) and (4) is market-adjusted buy-and-hold returns over the 180 days following transaction date (*Buy and hold return* (*BHR*)). For sales transactions, abnormal returns are multiplied by -1. *Innovation by competitors* is the ratio of the sum of the market value of competitor innovations over the sum of competitors' total assets two days before transaction dates. *Treatment index* is the book-value weighted average of the indicator value for competitors. The indicator value equals 1 if a competitor is headquartered in California, Delaware, Illinois, Kansas, Minnesota, North Carolina, Utah, or Washington. *Post 3 years* (*Pre 3 years*) is an indicator variable that equals 1 if a transaction is executed 2 years after (3 years before) 2008 and 0 otherwise. *Post_1, Post_2,* and *Post3* (*Pre_1, Pre_2,* and *Pre_3*) are indicator variables that equal 1 if a transaction is executed in 2008, 2009, or 2010 (2007, 2006, or 2005) and 0 otherwise. The appendix provides detailed definitions of the variables. *P*-values reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**TABLE 5**

**Trading profitability and Innovation by competitors: Robustness**

Panel A. Changing the time gap between transaction dates and competitors' innovation disclosure dates

| | t-1 | | t+7 | | t+14 | |
|---|---|---|---|---|---|---|
| | Carhart alpha | BHR | Carhart | BHR | Carhart | BHR |
| Independent variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Innovation by competitors | 0.003 | 0.004 | 0.031*** | 0.044*** | 0.031** | 0.051*** |
| | (0.894) | (0.870) | (0.001) | (0.001) | (0.018) | (0.005) |
| Controls (same as Table 3) | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.293 | 0.291 | 0.299 | 0.296 | 0.317 | 0.307 |
| Observations | 627,522 | 627,522 | 589,408 | 589,408 | 703,843 | 703,843 |

Panel B. Changing the definition of competitors

| | Hoberg and Phillips | | Fluidity | | Similarity | |
|---|---|---|---|---|---|---|
| Innovation by competitors | 0.014 | 0.043** | | | | |
| | (0.306) | (0.045) | | | | |
| Innovation by competitors (High) | | | 0.026* | 0.053** | 0.015 | 0.040** |
| | | | (0.054) | (0.020) | (0.209) | (0.040) |
| Innovation by competitors (Low) | | | -0.025 | -0.029 | -0.015 | -0.036 |
| | | | (0.205) | (0.294) | (0.540) | (0.371) |
| Controls (same as Table 3) | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.295 | 0.293 | 0.296 | 0.294 | 0.296 | 0.293 |
| Observations | 663,234 | 663,234 | 663,234 | 663,234 | 663,234 | 663,234 |

Panel C. Aggregating transactions

| | Firm-insider-transaction date | | Firm-transaction date | |
|---|---|---|---|---|
| | Carhart alpha | BHR | Carhart alpha | BHR |
| | (1) | (2) | (3) | (4) |
| Innovation by competitors | 0.024*** | 0.030*** | 0.019** | 0.023** |
| | (0.008) | (0.007) | (0.024) | (0.025) |
| Controls (same as Table 3) | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.206 | 0.211 | 0.197 | 0.201 |
| Observations | 175,958 | 175,958 | 144,272 | 144,272 |

Panel A (B, and C) presents estimates obtained from ordinary least square (OLS) regressions of trading profitability after changing the time gap between transaction dates and competitors' innovation disclosure dates (by changing the definition of competitors, or by aggregating transactions at the firm-insider-transaction-date level or the firm-transaction-date level). The sample consists of 703,843 insider sales executed from 2003 through 2020. For Panel A, and B (C), the dependent variable for columns (1), (3), and (5) ((1) and (3) is *Carhart alpha*, and the dependent variable for columns (2), (4), and (6) ((2), and (4)) is *BHR*. For columns (1) and (2) ((3) and (4), (5) and (6)) of Panel A, we use insider sales one day before (from day 2 to 7 after, from day 2 to 14 days after) innovation announcement dates. For columns (1) and (2) of Panel B, we estimate the innovation by competitors by replacing competitors operating in the same SIC three-digit industry with those operating in the same TNIC industry of Hoberg and Philips (2016). For columns (3) and (4) (columns (5) and (6)) we estimate innovation by competitors (High) ((Low)) using competitors with higher (lower) fluidity (similarity) values than the median value for each focal firm. For Panel C we aggregate insider sales at the firm-insider-transaction-date level for columns (1) and (2) and at the firm-transaction-date level for columns (3) and (4). The appendix provides detailed definitions of the variables. *P*-values reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 6**
**Effect of negative externality: Insider sales vs. Insider silence**

| | Sales growth | Patent filing | Trade secrecy |
|---|---|---|---|
| | OLS | OLS | Probit |
| Independent variable | (1) | (2) | (3) |
| Innovation | 0.313** | 1.145*** | 1.576*** |
| | (0.040) | (0.000) | (0.003) |
| Competitor innovation accompanied by insider silence | -0.359 | 0.642** | 3.365*** |
| | (0.142) | (0.038) | (0.000) |
| Competitor innovation accompanied by insider sales | -0.490* | 0.284 | 2.807* |
| | (0.062) | (0.594) | (0.067) |
| Log (firm size) | -0.049*** | 0.094*** | 0.024 |
| | (0.000) | (0.000) | (0.143) |
| MB | 0.002 | 0.003*** | 0.015*** |
| | (0.171) | (0.003) | (0.000) |
| Returns | 0.078*** | 0.005 | 0.016 |
| | (0.000) | (0.347) | (0.382) |
| Idiosyncratic volatility | -1.971*** | -1.197*** | 4.350*** |
| | (0.000) | (0.000) | (0.000) |
| Leverage | 0.037 | -0.048 | -0.229*** |
| | (0.318) | (0.163) | (0.005) |
| ROA | -0.163*** | -0.042 | -0.439*** |
| | (0.000) | (0.175) | (0.000) |
| R&D intensity | 0.061*** | -0.002 | 0.021* |
| | (0.000) | (0.304) | (0.054) |
| Loss | 0.022** | -0.007 | 0.097*** |
| | (0.050) | (0.555) | (0.005) |
| R&D indicator | -0.050* | 0.064** | 0.689*** |
| | (0.094) | (0.042) | (0.000) |
| Institutional ownership | 0.019 | 0.050 | 0.471*** |
| | (0.460) | (0.176) | (0.000) |
| Firm fixed effects | Yes | Yes | No |
| Industry fixed effect | No | No | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.301 | 0.301 | |
| Pseudo $R^2$ | | | 0.332 |
| Observations | 22,195 | 22,195 | 22,482 |

This table presents estimates obtained from ordinary least square (probit) regressions of future sales growth and the number of patents (Trade secrecy) on *Competitor innovation accompanied by silence* and *Competitor innovation accompanied by insider sales*. The sample consists of 22,482 firm-years executed from 2003 through 2020. The dependent variable is future sales growth in one year for column (1), patent filing for column (2), and trade secrecy for column (3). *Innovation* is the market value of innovations for a firm in each year. *Competitor innovation accompanied by insider sales* (C*ompetitors innovation accompanied by insider silence*) is the market value of competitor innovations of a focal firm in each year when insiders in the firm execute (do not execute) sales. We define competitors as firms whose industry codes (SIC 3-digit) are the same as the focal firm's. We use SIC 3-digit industry classifications to control for industry fixed effects. The appendix provides detailed definitions of the variables. *P*-values reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 7**
**Follow-on innovation: Knowledge-spillover channel**

| | Patent filing | | Trade secrecy | |
|---|---|---|---|---|
| | OLS | | Probit | |
| Independent variable | (1) | (2) | (3) | (4) |
| Innovation | 1.118*** | 1.122*** | 1.482*** | 1.498*** |
| | (0.000) | (0.000) | (0.003) | (0.003) |
| Competitor innovation (a) | 0.016 | | 3.512*** | |
| | (0.966) | | (0.000) | |
| (a)*(d) | 0.081*** | | -0.151*** | |
| | (0.003) | | (0.007) | |
| Competitor innovation accompanied by insider silence (b) | | 0.051 | | 3.674*** |
| | | (0.893) | | (0.000) |
| (b)*(d) | | 0.082*** | | -0.160*** |
| | | (0.002) | | (0.003) |
| Competitor innovation accompanied by insider sales (c) | | -0.234 | | 2.657 |
| | | (0.711) | | (0.169) |
| (c)*(d) | | 0.074* | | -0.110 |
| | | (0.088) | | (0.330) |
| Log(1+Spillover) (d) | -0.003 | -0.003 | 0.016*** | 0.016*** |
| | (0.111) | (0.111) | (0.000) | (0.000) |
| Controls (same as Table 7) | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | No | No |
| Industry fixed effect | No | No | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.863 | 0.863 | | |
| Pseudo $R^2$ | | | 0.334 | 0.334 |
| Observations | 22,195 | 22,195 | 22,482 | 22,482 |

This table presents estimates obtained from ordinary least square (probit) regressions of the number of patents (Trade secrecy) that depend on knowledge spillovers. The sample consists of 22,482 firm-years from 2003 through 2020. For columns (1) and (2), the dependent variable is patent filing. For columns (3) and (4), the dependent variable is trade secrecy. *Innovation* is the market value of innovations for a firm in each year. *Competitor innovation accompanied by insider sales* (*Competitor innovation accompanied by insider silence*) is the market value of innovations for competitors of a focal firm in each year when insiders in the firm execute (do not execute) sales. *Competitor innovation* is the market value of innovations for competitors of a focal firm in each year. *Log(1+Spillover)* is the logarithmic value of 1+technology spillover and technology spillover is defined following Tseng (2022). We define competitors as firms whose industry codes (SIC 3 digit) are the same as the focal firm's. We use SIC 3-digit industry classifications to control for industry fixed effects. The appendix provides detailed definitions of the variables. *P*-values reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 8**
**Follow-on innovation in a competitive industry**

| | Concentrated | Competitive | Concentrated | Competitive | Concentrated | Competitive |
|---|---|---|---|---|---|---|
| Independent variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Innovation | 1.036*** | 1.009*** | 1.026*** | 0.968*** | 1.032*** | 0.965*** |
| | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | (0.001) |
| Competitor innovation accompanied by insider silence (a) | 0.372 | 0.840** | | | 0.225 | -0.019 |
| | (0.454) | (0.028) | | | (0.695) | (0.968) |
| Competitor innovation accompanied by insider sales (b) | -0.233 | 0.735 | | | -0.560 | 0.308 |
| | (0.768) | (0.350) | | | (0.532) | (0.744) |
| Competitor innovation (c) | | | 0.123 | 0.023 | | |
| | | | (0.831) | (0.963) | | |
| (c)*(d) | | | 0.030 | 0.100*** | | |
| | | | (0.481) | (0.005) | | |
| (a)*(d) | | | | | 0.027 | 0.105*** |
| | | | | | (0.516) | (0.004) |
| (b)*(d) | | | | | 0.046 | 0.060 |
| | | | | | (0.501) | (0.337) |
| Log(1+Spillover*)* (d) | | | -0.002 | -0.003 | -0.002 | -0.003 |
| | | | (0.517) | (0.227) | (0.512) | (0.231) |
| Controls (same as Table 7) | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.897 | 0.816 | 0.897 | 0.817 | 0.897 | 0.817 |
| Observations | 11,754 | 9,790 | 11,754 | 9,790 | 11,754 | 9,790 |

This table presents estimates obtained from ordinary least square (probit) regressions of the number of patents (Trade secrecy) based on competitive industry and concentrated industry. The sample consists of 22,195 firm-years from 2003 through 2020. The dependent variable is patent filing. *Innovation* is the market value of innovations for a firm in each year. We divide the sample based on the median value of *Lerner index* and define concentrated industry (competitive industry) as the sample with a higher (lower) value of *Lerner index*. *Competitor innovation accompanied by insider sales* (*Competitor innovation accompanied by insider silence*) is the market value of innovations for competitors of a focal firm in each year when insiders in the firm execute (do not execute) sales. *Competitor innovation* is the market value of innovations for competitors of a focal firm in each year. *Log(1+Spillover)* is the logarithmic value of 1+technology spillover and technology spillover is defined following Tseng (2022). We define competitors as firms whose industry codes (SIC 3 digit) are the same as the focal firm's. We use SIC 3-digit industry classifications to control for industry fixed effects. The appendix provides detailed definitions of the variables. *P*-values reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 9**
**Follow-on innovation: Growth firm vs. Value firm**

| | Growth | Value | Growth | Value |
|---|---|---|---|---|
| Independent variable | (1) | (2) | (3) | (4) |
| Innovation | 0.886*** | 1.709*** | 0.894*** | 1.718*** |
| | (0.000) | (0.005) | (0.000) | (0.005) |
| Competitor innovation (a) | -0.151 | 0.080 | | |
| | (0.766) | (0.874) | | |
| (a)*(d) | 0.077** | 0.064 | | |
| | (0.028) | (0.104) | | |
| Competitor innovation accompanied by insider silence (b) | | | -0.064 | 0.080 |
| | | | (0.898) | (0.872) |
| (b)*(d) | | | 0.085** | 0.057 |
| | | | (0.013) | (0.159) |
| Competitor innovation accompanied by insider sales (c) | | | -0.644 | 0.206 |
| | | | (0.417) | (0.867) |
| (c)*(d) | | | 0.038 | 0.098 |
| | | | (0.534) | (0.132) |
| Log(1+Spillover) (d) | -0.000 | -0.005* | -0.000 | -0.005* |
| | (0.937) | (0.094) | (0.960) | (0.098) |
| Controls (same as Table 7) | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.875 | 0.854 | 0.875 | 0.854 |
| Observations | 10,636 | 10,649 | 10,636 | 10,649 |

This table presents estimates obtained from ordinary least square (probit) regressions of the number of patents (Trade secrecy) that depend on knowledge spillovers. The sample consists of 22,482 firm-years from 2003 through 2020. For columns (1) and (2), the dependent variable is patent filings. For columns (3) and (4), the dependent variable is trade secrecy. *Innovation* is the market value of innovations for a firm in each year. We divide the sample based on the median value of the market-to-book ratio (*MB*) and define growth firms (value firms) as the sample with higher (lower) values of *MB*. *Competitor innovation accompanied by insider sales* (*Competitor innovation accompanied by insider silence*) is the market value of innovations for competitors of a focal firm in each year when insiders in the firm execute (do not execute) sales. *Competitor innovation* is the market value of innovations for competitors of a focal firm in each year. *Log(1+Spillover)* is the logarithmic value of 1+technology spillover and technology spillover is defined following Tseng (2022). We define competitors as firms whose industry codes (SIC 3 digit) are the same as the focal firm's. We use SIC 3-digit industry classifications to control for industry fixed effects. The appendix provides detailed definitions of the variables. *P*-values reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

## Appendix: Variable definitions

| Variable | Definition |
|---|---|
| **Key independent variables:** | |
| Innovation by competitors | First, we estimate the innovation value of each firm on each issuance date by estimating the average market value of innovations on the same date, from Kogan et al. (2017). Second, we estimate the innovation value of competitors by estimating the ratio of the sum of all competitors' innovation values over the sum of the book values of their total assets on each issuance date. We define competitors as firms whose industry codes (SIC 3 digit) are the same as the focal firm's. |
| Innovation by local (non-local) competitors | We divide *Innovation by competitors* into *Innovation by local competitors* and *Innovation by non-local competitors* based on the median average local distance between a focal firm and its competitors. For each issuance date, we estimate the distance between a focal firm and its competitors that announce innovations and calculate the average distance. To estimate the distance, we use kilometers (km) and a same-state dummy variable that equals 1 if each focal firm and competitor pair is located in the same state. |
| Innovation by competitors (High) or (Low) | We divide *Innovation by competitors* into *Innovation by competitors* (*High*) and *Innovation by competitors* (*Low*) based on the median of either product fluidity or product similarity for each focal firm's competitors. For each issuance date we find a focal firm's competitors based on the TNIC from Hoberg and Philips (2016) and calculate the median values of either product fluidity or product similarity. We then estimate *Innovation by competitors* (*High*) and *Innovation by competitors* (*Low*) using competitors above and below the median values, respectively. We require at least 4 competitors for each focal firm. |
| Competitor innovation accompanied by insider sales (silence) | We estimate the innovation value of competitors by estimating the ratio of the sum of all competitors' innovation values over the sum of the book values of their total assets in each year. We then decompose it into competitor innovation accompanied by insider sales (silence) if insiders do (not) execute sales transactions in that year. |
| **Firm characteristics:** | |
| Board independence | Ratio of the number of independent directors to the total number of directors on a firm's board. |
| Herfindal-Hershman Index (HHI) | HHI is defined as, $\sum_{i=1}^{I} s_{ij}^2$, where $s_{ij}$ is the market share of firm *i* in industry *j* using sales. Following Hou and Robinson (2006), we estimate the 3-year moving average. |
| Idiosyncratic volatility | Daily idiosyncratic volatility from the Fama-French three-factor model over the preceding year. |
| Innovation | Following Kogan et al. (2017), we estimate the innovation value of each firm by aggregating the market value of innovations in year *t*, divided by total assets. |
| Institutional ownership | Ratio of the number of shares held by institutions to the total number |

| | |
|---|---|
| | of shares outstanding in the most recent filings before transactions |
| Lerner Index | Following Gaspar and Massa (2005) and Peress (2010), we estimate the Lerner index in two steps. First, we estimate a firm's operating profit margin, sales minus costs (cost of goods sold, and general and administrative expenses) by sales. Second, we subtract the industry average of the profit margin from the profit margin to control for structural differences across industries. |
| Leverage | Total liabilities/Total assets |
| Log (firm Size) | Natural logarithm of total assets |
| Log (Total Compensation) | Natural logarithm of CEO total compensation |
| Loss | Indicator variable that equals 1 if income before extraordinary items is negative and 0 otherwise. |
| MB | Ratio of the market value of equity to the book value of equity. |
| Patent filing | Log(1+the number of patent in each year). If the number of patents in each year is missing, we replace it with zero. |
| Returns | Cumulative stock returns over the last one year skipping one month. |
| R&D intensity | R&D expenditure/Sales |
| R&D dummy | Indicator variable that equals 1 if R&D expenditures is not missing and 0 otherwise. |
| ROA | Income before extraordinary items/lagged total assets |
| Sales growth | (sales in year *t* – sales in year *t*-1)/sales in year *t*-1 |
| Trade secrecy | Equals 1 if insider's firm discloses "trade secrecy" or "trade secret" from 10-K filings on SEC's EDGAR database and 0 otherwise. Glaeser (2018). |
| Technology-linked peers | Following Jaffe (1986) and Bloom et al. (2013), we estimate pairwise technology closeness ($Tech_{ijt}$), the uncentered correlation of patent distributions between all pairs of firm *i* and firm *j*, as follows, $$Tech_{ijt} = \frac{T_{it}T'_{jt}}{(T_{it}T'_{jt})^{\frac{1}{2}}(T_{it}T'_{jt})^{\frac{1}{2}}}$$ where $T_{it} = (T_{it1}, T_{it2}, \ldots, T_{it678})$ is a vector of firm $i$'s proportional share of patents across 678 cooperative patent classifications (CPC) over the rolling preceding five years as of time *t*. We use Match_patent_permco_permno_2022.csv and Match_patent_cpc_2022.csv for firm identifier and technology class, respectively. We estimate the proportional share of patents in two steps. First, we assign 1 to the corresponding CPC for each patent. Otherwise, we assign 0. Each patent may have multiple technology classifications. In this case, we assign 1 to those with multiple corresponding classifications. Second, for every five years we aggregate all numbers and divide by the aggregation for each firm. Technology closeness is between 0 and 1 and is symmetric. The technology-linked peer is defined as any firm *j* with non-0 technology closeness to a focal firm *i*. |
| Log(1+Spillover) | Following Tseng (2022), technology spillover is defined as |

| | |
|---|---|
| | $Spillover_{it} = \sum_j Tech_{ijt} * G_{jt}$ where $Tech_{ijt}$ is the technology closeness between firm *i* and *j* in year *t*, and $G_{jt}$ is the amount of R&D stock firm *j* holds in year *t*. The amount of R&D stock is estimated with the inventory method as follows, $$G_{jt} = R\&D_{jt} + (1-\delta) * G_{jt-1},$$ where $R\&D_{jt}$ is R&D expenditures by firm *j* in year *t*, and $\delta$ is the depreciation rate of 0.15. Technology spillover is then the logarithmic value of 1+$Spillover_{it}$. |
| **Transaction characteristics:** | |
| BHR | Market-adjusted buy-and-hold returns over the 180 days following transaction dates. For sales transactions, buy-and-hold returns are multiplied by -1. |
| Blackout period (indicator) | Equals 1 if a transaction occurs in the blackout period (i.e., the calendar day window (-46,1), where day 0 is the quarterly earnings announcement date) and 0 otherwise. |
| Carhart alpha (%) | Average daily alpha (intercept) from the four-factor Fama and French (1993) and Carhart (1997) model estimated over 180 days following transaction dates, reported in percentages. For sales transactions, Carhart alpha is multiplied by -1. |
| Equity ownership by each trader | Equity ownership by each trader before transactions. |
| Past return | Market-adjusted buy-and-hold returns over 180 days prior to transaction dates. We require the number of trading days to be above 60. |
| Transaction size | Absolute value of the net number of stocks purchased by all insiders on a given transaction date divided by the total number of shares outstanding. |

**TABLE A.1**
**Distribution of sales transactions to hedge against competitor innovation by year and industry**

| Year | Agriculture, forestry, and fisheries (01–09) | Mineral industries and construction (10–17) | Manufacturing (20–39) | Transportation and communications (40–48) | Wholesale trade and retail trade (50–59) | Service industries (70–89) | Public Administration and Non-classifiable Establishments (90-99) | Total |
|---|---|---|---|---|---|---|---|---|
| 2003 | 0 | 52 | 2,449 | 52 | 22 | 1063 | 0 | 3,638 |
| | (0.00) | (0.11) | (0.19) | (0.04) | (0.01) | (0.16) | (0.00) | (0.09) |
| 2004 | 0 | 112 | 2,032 | 40 | 68 | 742 | 3 | 2,997 |
| | (0.00) | (0.07) | (0.14) | (0.02) | (0.02) | (0.08) | (0.09) | (0.06) |
| 2005 | 1 | 40 | 2,176 | 103 | 111 | 2243 | 0 | 4,674 |
| | (0.02) | (0.02) | (0.17) | (0.05) | (0.01) | (0.16) | (0.00) | (0.08) |
| 2006 | 1 | 30 | 3,430 | 132 | 45 | 2676 | 2 | 6,316 |
| | (0.00) | (0.01) | (0.18) | (0.05) | (0.01) | (0.13) | (0.67) | (0.08) |
| 2007 | 0 | 302 | 6,065 | 205 | 163 | 3093 | 0 | 9,828 |
| | (0.00) | (0.05) | (0.20) | (0.05) | (0.02) | (0.15) | (0.00) | (0.09) |
| 2008 | 0 | 124 | 5,498 | 134 | 33 | 1679 | 0 | 7,468 |
| | (0.00) | (0.02) | (0.23) | (0.06) | (0.01) | (0.14) | (0.00) | (0.09) |
| 2009 | 1 | 54 | 1,564 | 49 | 57 | 973 | 0 | 2,698 |
| | (0.03) | (0.03) | (0.32) | (0.06) | (0.01) | (0.14) | (0.00) | (0.09) |
| 2010 | 0 | 43 | 1,084 | 20 | 51 | 749 | 0 | 1,947 |
| | (0.00) | (0.02) | (0.19) | (0.03) | (0.01) | (0.12) | (0.00) | (0.08) |
| 2011 | 8 | 47 | 1,078 | 51 | 53 | 723 | 0 | 1,960 |
| | (0.28) | (0.03) | (0.18) | (0.07) | (0.01) | (0.15) | (0.00) | (0.08) |
| 2012 | 5 | 120 | 1,065 | 97 | 50 | 613 | 0 | 1,950 |
| | (0.22) | (0.08) | (0.18) | (0.07) | (0.01) | (0.14) | (0.00) | (0.08) |
| 2013 | 8 | 66 | 1,088 | 110 | 83 | 1114 | 0 | 2,469 |
| | (0.02) | (0.06) | (0.18) | (0.06) | (0.03) | (0.31) | (0.00) | (0.10) |
| 2014 | 5 | 106 | 1,031 | 78 | 27 | 718 | 0 | 1,965 |
| | (0.16) | (0.08) | (0.20) | (0.05) | (0.01) | (0.12) | (0.00) | (0.08) |
| 2015 | 3 | 25 | 860 | 49 | 50 | 462 | 0 | 1,449 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (0.10) | (0.04) | (0.20) | (0.06) | (0.02) | (0.12) | (0.00) | (0.08) |
| 2016 | 1 | 30 | 455 | 41 | 23 | 372 | 0 | 922 |
| | (0.05) | (0.04) | (0.18) | (0.06) | (0.02) | (0.14) | (0.00) | (0.08) |
| 2017 | 1 | 51 | 657 | 67 | 31 | 430 | 0 | 1,237 |
| | (0.05) | (0.07) | (0.19) | (0.08) | (0.02) | (0.11) | (0.00) | (0.08) |
| 2018 | 0 | 19 | 271 | 21 | 5 | 167 | 0 | 483 |
| | (0.00) | (0.05) | (0.15) | (0.09) | (0.01) | (0.09) | (0.00) | (0.07) |
| 2019 | 0 | 10 | 537 | 39 | 11 | 296 | 0 | 893 |
| | (0.00) | (0.02) | (0.19) | (0.10) | (0.01) | (0.07) | (0.00) | (0.07) |
| 2020 | 0 | 0 | 78 | 0 | 6 | 24 | 0 | 108 |
| | (0.00) | (0.00) | (0.13) | (0.00) | (0.02) | (0.03) | (0.00) | (0.05) |
| Total | 34 | 1,231 | 31,418 | 1,288 | 889 | 18,137 | 5 | 53,002 |
| | (0.02) | (0.04) | (0.10) | (0.05) | (0.01) | (0.10) | (0.05) | (0.08) |

This table presents the distribution of the number of sales transactions by year and industry, executed by insiders after their competitors announce innovations. We define sales transactions driven by competitor innovation announcements as the execution by an insider of a sales transaction 2 days after the competitor's innovation announcement. The sample consists of 53,002 transactions driven by competitor innovation announcements among a total of 631,984 transactions executed from 2003 through 2020. The numbers in brackets indicate the percentages of sales transactions executed by insiders after their competitors announce innovations over the number of total sales transactions in each year and industry.

**Table A.2**
**Correlation matrix**

| | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Carhart alpha (%): a | 1 | | | | | | | | | | | | | | | |
| Buy and hold return: b | 0.88 | 1 | | | | | | | | | | | | | | |
| Innovation by competitors: c | 0.00 | -0.01 | 1 | | | | | | | | | | | | | |
| Log (firm size): d | 0.04 | 0.05 | -0.06 | 1 | | | | | | | | | | | | |
| MB: e | 0.06 | 0.03 | 0.03 | -0.12 | 1 | | | | | | | | | | | |
| ROA: f | -0.02 | -0.03 | -0.01 | 0.12 | 0.02 | 1 | | | | | | | | | | |
| Investment/total asset: g | -0.02 | -0.02 | 0.00 | 0.08 | 0.03 | 0.05 | 1 | | | | | | | | | |
| R&D/Sales: h | 0.01 | 0.00 | 0.04 | -0.16 | 0.18 | -0.35 | -0.18 | 1 | | | | | | | | |
| Stock return volatility: i | -0.02 | 0.00 | 0.04 | -0.53 | 0.06 | -0.26 | 0.02 | 0.17 | 1 | | | | | | | |
| Analyst dispersion: j | 0.03 | 0.01 | 0.01 | -0.13 | 0.10 | -0.34 | 0.03 | 0.16 | 0.20 | 1 | | | | | | |
| Institutional ownership: k | 0.04 | 0.04 | -0.01 | 0.19 | -0.05 | -0.02 | 0.03 | -0.03 | -0.23 | 0.00 | 1 | | | | | |
| Board independence: l | 0.06 | 0.05 | -0.01 | 0.17 | 0.06 | -0.07 | -0.11 | 0.01 | -0.12 | -0.01 | 0.20 | 1 | | | | |
| Equity ownership by each trader: m | 0.02 | 0.02 | 0.02 | -0.17 | 0.11 | 0.06 | -0.05 | 0.00 | 0.13 | -0.01 | -0.34 | -0.08 | 1 | | | |
| Transaction size: n | 0.00 | 0.01 | 0.00 | -0.15 | -0.06 | 0.02 | 0.00 | -0.10 | 0.11 | 0.01 | 0.04 | -0.08 | 0.12 | 1 | | |
| Blackout period: o | 0.01 | 0.02 | 0.02 | -0.02 | -0.02 | -0.03 | 0.02 | -0.03 | 0.02 | 0.00 | 0.02 | 0.00 | 0.00 | -0.01 | 1 | |
| Past return: p | -0.06 | -0.06 | 0.02 | -0.14 | 0.02 | -0.08 | 0.06 | 0.01 | 0.25 | 0.07 | -0.04 | -0.05 | 0.01 | 0.15 | -0.03 | 1 |

**Table A.3**
**Product-market competition channel: Geographic distance from innovative competitors**

| | Kilometers (km) | | Same State | |
|---|---|---|---|---|
| | Carhart alpha | BHR | Carhart alpha | BHR |
| Independent variable | (1) | (2) | (3) | (4) |
| Innovation by local competitors | 0.079** | 0.132*** | 0.081*** | 0.125*** |
| | (0.012) | (0.005) | (0.008) | (0.003) |
| Innovation by non-local competitors | 0.030 | 0.050 | 0.036 | 0.069** |
| | (0.205) | (0.113) | (0.187) | (0.048) |
| Controls (same as Table 3) | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.293 | 0.292 | 0.293 | 0.292 |
| Observations | 631,890 | 631,890 | 631,890 | 631,890 |

This table presents estimates obtained from ordinary least square (OLS) regressions of trading profitability based on geographic distance between a focal firm and its competitors. The sample consists of 631,890 insider sales executed from 2003 through 2020. The dependent variable for columns (1) and (3) is *Carhart alpha* and the dependent variable for columns (2) and (4) is *BHR*. For columns (1) and (2) we estimate the average distance between a focal firm and its competitors in kilometers (km). For columns (3) and (4) we estimate the average value between a focal firm and its competitors based on a same-state dummy variable that equals 1 if each focal firm and competitor pair is located in the same state. The appendix provides a detailed definitions of the variables. *P*-values reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.