Knowledge spillover, market efficiency, and innovation disclosure: Role of the insider trading

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Abstract

We examine whether insiders exploit the information friction of knowledge spillover in their transactions, and how their transactions affect the knowledge spillover and innovation disclosure. Using the past returns of technology-linked peers (*Techret*), insiders earn higher abnormal profits from purchase transactions. Employing the 2008 Federal Circuit (FC) ruling that shifted invention property rights to employers as an exogenous shock, we find the profitability increases when the peers with new patents are headquartered in the FC states. The profitability is larger when peer firms disclose less trade secrecy, when peer firms are closely located, when insiders have the education ties, and when the knowledge capital is large. Information asymmetry and legal risk increase the profitability. The trading volume and opportunistic trading increase when *Techret* increases. Further, the purchase transactions following *Techret* increases the knowledge dissemination and the market efficiency by subsuming the return predictability of *Techret*, and predicting future stock returns. Lastly, the purchase transactions affect the strategic disclosure by reducing the trade secrecy and increasing the patent quality.

***Keywords**:* Knowledge spillover, Insider trading, Information friction of knowledge spillover, Market efficiency, Technology momentum, Innovation disclosure

***JEL Classification**:* D23, G14, G30, O31, O32

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1. Introduction

Knowledge spillover is a positive externality driving technological innovation and economic growth (Jaffe, 1986; Jaffe, Trajtenberg, and Henderson, 1993; Bloom, Schankerman, and Van Reenen, 2013; Aghion and Jaravel, 2015; Kogan et al., 2017). While innovation is proprietary and confidential, the innovation disclosure allows others to access the forefront knowledge of innovation with sufficient details from inventors, and such partial excludability, which is the inability of innovation owners to fully limit the access by others (Romer, 1990; Glaeser and Lang, 2024)[1], drives the knowledge spillover (Bloom, Schankerman, and Van Reenen, 2013; Kim and Valentine, 2021; Tseng and Zhong, 2024). However, knowledge dissemination via patent disclosure has the information frictions. First, knowledge spillover is limited in the same technology space. The literature finds that "technology closeness" drives the positive externality (Jaffe, 1986; Bloom, Schankerman, and Van Reenen, 2013).[2] Second, patent disclosure is the strategic decision due to its proprietary costs (Lansford, 2006; Glaeser, 2018; Glaeser and Landsman, 2021).[3] Managers selectively disclose the proprietary information, and the spillover might be restricted. These raise several interesting questions. The first question is whether any informed agents exploit such information frictions in the stock market. The second question is whether their exploit expedites the dissemination of proprietary information to the stock market,

[1] Romer (1990) documents two distinguishing features of technology, compared to the conventional economic good: non-rivalry and partial excludability. Non-rivalry refers to the property that its use by one firm or person in no way limits its use by another. Partial excludability refers to the incomplete function of preventing others from using it. Glaeser and Lang (2024) document those features and their implications on the accounting literature.

[2] Jaffe (1986) measures the technology proximity between firms using the distribution of patents over patent class. This approach is widely used in the literature (Bloom, Schankerman, and Van Reenen, 2013; Lee et al., 2019; Tseng, 2022; Tseng and Zhong, 2024).

[3] Patent disclosure incurs the proprietary cost due to the partial excludability of innovation. The literature document that managers exercise the discretion between patent disclosure and trade secrecy (Landsford, 2006; Glaeser, 2018; Glaerser, Michels, and Verrecchia, 2020; Glaeser and Landsman, 2021; Chang, Tseng, and Yu, 2024).

and improve the knowledge spillover. The last question is whether their exploit changes managers' disclosure decision since it might incur the proprietary cost of innovation.

In this paper, we try to answer these questions by using the technology momentum from Lee et al. (2019). They find that the past returns of technology-related peers (*Techret*) predict future returns of focal firms due to the slow dissemination of knowledge spillover. This lead and lag relationship captures the information friction of knowledge spillover, which is driven by either the difficulty of sharing technology closeness or the strategic disclosure decision due to the proprietary cost[4]. Specifically, we hypothesize that insiders make the abnormal profits by exploiting the information friction about knowledge spillover. Further, we expect that their transactions increase the speed of knowledge dissemination and improve the market efficiency by expediting stocks reflecting knowledge spillover in time. Lastly, their transactions affect the strategic disclosure by reducing the trade secrecy and increasing the patent quality because the proprietary cost is already realized via the insider trading.

We investigate the insider trading for two reasons. First, the inside trading is closely related to the proprietary costs. The inside transaction is one of important mechanism to convey the private information to financial markets (Jaffe, 1975; Finnerty, 1976; Rozeff, and Zaman, 1988; Ravina and Sapienza, 2009; Cohen et al., 2012). Choi et al. (2024) find that the majority of insider trading policies are designed to protect the proprietary information, and that the proprietary costs lower the insider trading. In other words, the insider trading disseminates the proprietary information to the market, and affects the knowledge spillover. Since the patent disclosure provides incomplete protection on innovation, the insider trading incurs proprietary costs.

[4] Lee et al. (2019) estimate the technology closedness-weighted average past returns of technology-linked peers, which shares the same patent class over the last five years. They find that it predicts future returns of focal firms, and the predictability is stronger particularly when the proprietary cost, proxied by R&D or patent, is high.

Second, insiders have the information advantage of the frictions about knowledge spillover. Innovation is the long-term project requiring the understanding about novel idea or technology, resulting in the information asymmetry. As insiders, defined as officers, directors, or large shareholders under SEC regulation, their income is tightly linked to the long-term firm performance. They have the strong motive to comprehensively understand their innovation including the patent class, or the technology-related peers. Also, insiders are in positions to exercise the discretion over the patent disclosure policy to curb the dissemination of proprietary information, resulting in the information asymmetry. That said, insiders know the proprietary costs behind the strategic disclosure. These advantages allow insiders to exploit the frictions about knowledge spillover. In other words, the insider transaction might increase the speed of knowledge spillover. It is particularly important if the information friction drives the mispricing in the financial market because the insider trading reduces the friction, complements the partial excludability, and changes the disclosure behavior.

Empirically, we use *technology-linked return* (*Techret*) as a proxy for the information friction of knowledge spillover, following Lee et al. (2019). Lee et al. (2019) find the positive relation between returns of technology-linked firms (*tech peers*) and stock return of a focal firm in next month. We estimate *Techret* in two steps. First, we compute the pairwise technology closeness ($tech_{ijt}$), the uncentered correlation of the patent distributions between all pairs of firm *i* and firm *j*. This measure provides us how much two firms, *i* and *j*, have the similar technology space. Second, we compute *Techret* as the average monthly returns of technology-linked firms in the technology space, weighted by technology closeness. That is, *Techret* estimates the portfolio returns of peer firms which have the similar technology of a focal firm *i*. We assume that insiders engage in inside trading after they observe the technology-linked returns so we match insiders' transactions in next month of *Techret.* Our main findings are as follows.

First, we find that the insider trading profitability following *Techret* is significantly positive. That is, insiders make significant abnormal profits from their purchases after they observe the positive spillover news from their *tech peers*. Specifically, both Carhart four-factor alpha over 180 days (hereafter *Carhart*) and the market-adjusted six-month buy-and-hold return (hereafter *BHR*) are 1.89 percent and 1.52 percent with a change of one standard deviation of *Techret*, respectively. To address the endogeneity concerns, we implement the quasi-natural experiment by employing a Court of Appeals for the Federal Circuit ruling in 2008 (the 2008 FC ruling) (Suh, 2023). This state-level exogenous event shifted the patent property rights from inventor-employees to firms in the eight states[5], and thus firms headquartered in those eight states increase R&D expenses as well as innovation outputs after the 2008 FC ruling. This is plausibly exogeneous for a focal firm since its *tech peers* in the eight states make claims over employee inventions easier than before the FC ruling. We estimate the treatment index of *tech peers* with new patents in the eight states, and find that higher exposure to *tech peers* in the eight states (a higher treatment index score) significantly increases insiders' profitability following *Techret* over the three years following the 2008 FC ruling.

Next, we investigate how the knowledge spillover affects the abnormal profit. First, we testify the knowledge dissemination channels in two ways. Glaeser (2018) and Tseng (2022) finds that firms relying on the trade secrecy decreases the corporate transparency and knowledge spillover. We show that the predictability of *Techret* with respect to insiders' abnormal profits becomes stronger if *tech peers*' trade secrecy is lower. Second, Jaffe, Trajtenberg, and Henderson

[5] The eight states include California, Delaware, Illinois, Kansas, Minnesota, North Carolina, Utah, and Washington.

(1993) find that knowledge spillover is geographically localized. We find that the abnormal profits are stronger if the distance between *tech peers* and a focal firm is shorter.

Second, we explore how insiders collect and process the knowledge spillover earlier than others. Chevalier and Ellison (1999) and Gottesman and Morey (2006) find that fund managers who graduate from top universities enable to access and analyze precisely firms' private information due to their higher intelligence levels and stronger alumni networks, and thereby earn higher returns from their investments than those who do not. To the extent that insiders' personal attributes such as their education impact their trading profitability more than firm and trade characteristics (Hiller, Korczak, Korczak, 2015), we expect that insiders who graduate Ivy League schools (*Ivy league*) exploit the friction from the knowledge spillover precisely and quickly and thus, earn significantly higher profits. We find that the profitability is driven by insiders who graduate Ivy League schools. Also, we expect that insiders have better knowledge about innovation themselves to enjoy the knowledge spillover friction. We estimate the knowledge capital by following Peters and Taylor (2017), and find that the abnormal profits are higher when focal firms possess more R&D capital stocks. Additionally, we testify whether the industry expertise helps to process the knowledge spillover but it does not increase the profits. This echoes the finding of Bloom, Schankerman, and Van Reenen (2013) where the knowledge spillover exists in the similar technology space rather than in the similar product space.

Further, we examine two trading environments. We find that the profitability is larger when information asymmetry is higher by using firm size, idiosyncratic volatility, analyst dispersion, and bid-ask spared. Also, we examine how the litigation cost affects insider trading profitability. Using two legal risk measures from Kim and Skinner (2012) and Huang et al. (2019), we find that insiders earn excess returns when the legal risk is lower.

Our results are robust by changing the empirical specifications. First, we estimate *Techret* by changing the holding period of lagged returns from 6-, and 12-month. Second, we change the trading gap between *Techret* and inside trading from one-month to three-month. Also, we estimate *Techret* by changing the patent classification from minor class to major class. Third, we aggregate the inside transactions into firm-insider-date or firm-date level. Regardless of different specifications, we find that the profitability is significantly positive.

Turning to insiders' trading activity on *Techret*, we show that insiders increase their trading volume when *Techret* increases. Also, similar to Cohen et al. (2012) and Massa et al. (2015), we categorize insiders into routine and opportunistic insiders, and find that *Techret* increases with trading volume by opportunistic insiders. The results suggest that insiders increase their trading volume to fully use the delayed information of technology news from their peers.

Next, we explore whether the insider trading helps to address the information friction of knowledge spillover. Since *Techret* predicts future stock return of a focal firm due to the slow dissemination of knowledge spillover and insiders exploit the mispricing earlier than the financial market, the insider trading increases the market efficiency by expediting stocks to reflect the knowledge spillover, and increases the speed of knowledge dissemination. We make a firm-level indicator variable, *Purchase*, which equals to 1 if insiders engage the purchase transactions after *Techret* exists, and 0 otherwise. Then, we estimate Fama-MacBeth regressions. First, consistent with Lee et al. (2019), *Techret* significantly predicts the future return. Second and more importantly, we estimate the interaction term between *Purchase* and *Techret*, and show that the interaction term is significantly negative. This confirms that the information of *Techret* is reflected in the stock price simultaneously when insiders execute the transactions. Third, we see that

Purchase alone predicts next month stock return, suggesting that the insider trading against technology spillover delivers new information to the market.

Lastly, we explore how the insider trading changes the strategic disclosure policies. The proprietary cost of innovation affects the disclosure policy (Glaeser, 2018; Chang, Tseng, and Yu, 2024). Since *Techret* captures the slow dissemination of knowledge spillover and do not incur the proprietary cost yet, we find that higher *Techret* relates to more trade secrecy, less patent filing and less patent quality to protect the proprietary information. However, the insider transactions convey the proprietary information in time and realizes the proprietary costs. Then, we find that the insider trading reduces the trade secrecy and increases the patent disclosure to protect their innovation by granting the temporary legal monopoly.

Our study has the several contributions. First, our paper contributes on the knowledge spillover. The knowledge spillover is to related productivity and innovation (Jaffe, 1987; Jaffe, Trajtenberg, and Henderson, 1993), firm valuation (Bloom, Schankerman, and Van Reenen, 2013), labor market and employee's well-being (Aghion et al., 2016), asset prices (Lee et al, 2019; Tseng, 2022), corporate disclosure (Glaeser, 2018; Tseng and Zhong, 2024). While knowledge can be easily disseminated due to partial excludability, it is costly to enjoy the positive externality. It requires for a focal firm to stay in the close technology proximity (Jaffe, 1987). Also, the huge proprietary cost allows firms to selectively disclose technology (Glaeser, 2018). Those generates some information friction between informed and outside investors, and the slow dissemination of knowledge spillover (Lee et al., 2019). Our paper studies how such information friction affects the insiders' trading behavior, proprietary costs, and knowledge spillover. We find the empirical evidence where insiders exploit the information friction, and expedite the knowledge spillover.

Second, we extend the literature of the source of insider trading profitability. The literature finds that the profitability of inside transactions leverages the private information (Ke et al., 2003; Ravina and Sapienza, 2009; Cohen et al., 2012; Cao et al., 2015), or the pricing error before it is corrected (Rozeff, and Zaman, 1998; Piotroski and Roulstone, 2006; Alldredge and Cicero, 2015). We try to extend the literature by examining the pricing errors from the slow dissemination of technology spillover as a new source of insider trading profitability. Further, our research relates to the market efficiency of insider trading. It has been long debate whether the insider trading improves the market efficiency, or the price discovery (Jaffe, 1975; Finnerty, 1976; Rozeff, and Zaman, 1988; Piotroski and Roulstone, 2006; Tookes, 2008; Fernandes and Ferreira, 2009; Peress, 2010; Massa et al, 2015). Our study directly testifies the market efficiency of insider trading against technology momentum. Lee et al. (2019) find that the release of technology spillover news takes time to be reflected in stock prices, and the past returns of technology-linked peer firms predicts future return of a focal firm. Based on this relationship, we explore whether the insiders' transactions leveraging technology spillover increase the speed of information dissemination.

Third, our research relates to innovation and disclosure. Knowledge spillover is created via patent disclosure, which provide the incomplete legal protection of innovation in exchange of the related knowledge dissemination. This naturally increases the proprietary cost. Recent studies document the tensions between knowledge spillover and the proprietary cost, and its implication in capital market. Kim and Valentine (2021) find that peer firms' patent filing facilitates a focal firm's R&D investment. Hegde, Herkenhoff, and Zhu (2018) and Beyhaghi, Khashabi, and Mohammadi (2022) document that patent disclosure increases the price discovery and the analyst forecast. Also, the literature investigates how managers exercise some discretion over the timing and quality of patent disclosure. Lansford (2006) finds that the patent disclosure increases before the bad earnings announcement. Glaeser (2018) shows that the trade secrecy reduces patent filing. Glaeser and Landsman (2021) find that technology competition delays the patent disclosure while product competition increases it. Choi et al. (2024) find that the proprietary cost lower the insider trading. Chang, Tseng, and Yu (2024) show that the cheaper processing cost of financial disclosure reduces the paten filing and increase the trade secrecy. Our paper find that insiders trade their shares under the friction of knowledge spillover, and the insider trading affects the strategic disclosure among patent filing and trade secrecy since it realizes the proprietary costs to outside peer firms.

The remainder of the paper is organized as follows. In Section 2, we develop the main hypothesis. In Section 3, we describe the data, the construction of our key variables, summary statistics, and discuss the empirical model designs. Section 4 presents the main results for the insider trading about the knowledge spillover, economic channels, and the comprehensive cross-sectional studies. Section 5 discusses the trading volume and opportunistic trading. Section 6 present results for the market efficiency. Section 7 discusses the change of the disclosure policy. Finally, we summarize and present concluding remarks in Section 8.

2. Hypothesis development

Technology, or innovation is a novel idea with two distinguishing attributes, non-rivalry and partial excludability (Romer, 1990). Non-rivalry refers to the property that its use by one firm or person in no way limits its use by another, and partial excludability refers to the incomplete function of preventing others from using it. Although the patent disclosure provides the legal protection, these attributes allow other firms to access new innovation by the original inventor, resulting in knowledge spillover. The patent filing set by the United States Patent and Trademark

Office (USPTO) intends to knowledge dissemination via the patent disclosure as well.[6] However, there are two major frictions in knowledge dissemination.

First, even though innovators cannot fully exclude the access by peers, not all peers have the positive externality. Jaffe (1986) finds that the knowledge spillover works among peer firms which are "technologically" closed, and suggest to estimate the technology closedness based on the patent class. Higher the technology closedness, more knowledge spillover. In other words, the knowledge spillover has the technology barrier among peers. For example, Bloom, Schankerman, and Van Reenen (2013) find that knowledge spillover among product market competitors is smaller than that among peers in the same technology class.

Second, knowledge spillover incurs the proprietary cost for innovators since the patent disclosure imposes the potential threat of inventing follow-on innovation by competitors. This tension between knowledge spillover and proprietary cost shapes the strategic corporate disclosure by incentivizing managers to exercise some discretion over both quantity and quality of patent filing, timing of disclosure, and even trade secrecy (Lansford, 2006; Glaeser, 2018; Glaeser and Landsman, 2021). This tension reduces the corporate transparency, and restrict the knowledge dissemination.

Put together, these frictions make the information asymmetry through the slow dissemination of knowledge spillover. Lee et al. (2019) find that the past returns of technology-related peers (*techret*) predict higher future returns of focal firms, and that the predictability

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

increases if focal firms have higher proprietary costs, proxied by R&D expenditure or patent. That said, this lead-lag relationship captures the frictions about knowledge spillover.

Our goal is to examine whether insiders exploit the friction about knowledge spillover. Insiders have the advantage of the frictions about knowledge spillover. Innovation is a long-term project requiring diverse understanding and subjective evaluation on its future cash flow with high information asymmetry. Their income is tightly linked to the long-term performance. They have the strong motive to comprehensively impound all information relevant for their innovation, including the technology-related peers. Also, insiders are either in positions to exercise the discretion over the patent disclosure policy or near places where the discretion is decided. That said, insiders know the proprietary costs behind the strategic disclosure. These advantages allow insiders to exploit the frictions about knowledge spillover. Therefore, the main hypothesis is stated as follows,

Hypothesis 1. *Insiders purchase their shares when the friction about knowledge spillover is high, and the profitability of such transactions is significantly positive.*

Next, we investigate the trading volume. Insiders in firms with high proprietary cost refrain from trading their shares to avoid revealing the proprietary information in the stock market (Choi et al., 2024). However, if the information friction prevents the stock price from reflecting the knowledge spillover, insiders increase more transactions by exploiting the friction.

Hypothesis 2. *The trading volume of the inside transactions increase with the friction of knowledge spillover.*

Since the insiders leverage on the friction of knowledge spillover, the proprietary information will be disseminated. We investigate whether the insider trading expedites the knowledge dissemination via the stock market. Specifically, we testify whether the past returns of technology-linked peers predict future return of a focal firm, and more importantly, whether the insider trading exploiting the friction expedite the dissemination of knowledge spillover by lowering the return predictability.

Hypothesis 3. *The friction of knowledge spillover positively predicts future return of a focal firm. However, the lead-lag predictability becomes weaker when insiders engage transactions.*

Lastly, we investigate how the insider trading affects the patent disclosure. The tension between knowledge spillover and proprietary cost complicates the patent disclosure (Glaeser, 2018; Chang, Tseng, and Yu, 2024). Since *Techret* captures the friction of knowledge spillover and do not incur the proprietary cost yet, we hypothesize that higher *Techret* relies on more trade secrecy, less patent filing and quality to protect the proprietary information. However, if the insider transactions convey the proprietary information in time and realizes the proprietary costs, we expect that the insider trading reduces the trade secrecy and increases the patent filing to avoid the negative externality where the follow-on innovation by *tech peers* displaces the incumbent innovation by a focal firm since the patent disclosure provides the protection granting the temporary legal monopoly. The last hypothesis is as follows,

Hypothesis 4. *The friction of knowledge spillover decreases both quantity and quality of patent filing and increases the trade secrecy due to the proprietary cost. However, the insider trading revealing the proprietary information increases both quantity and quality of patent filing and decreases the trade secrecy.*

3. Research design

In this section, we describe the data, the measures of the friction of knowledge spillover and trading profitability, present the summary statistics, and design the empirical specifications.

Data

We obtain an initial sample of insider transactions over the period from 2001 to 2017 from Thomson Financial Insiders Data Feed (IDF). We limit our sample to transactions in firms listed on the NYSE, AMEX, or NASDAQ whose stock return and financial data are available in the Center for Research in Security Prices (CRSP) and Compustat, respectively. We focus only on valid open market purchase transactions of common shares without any amendments.[7] We further require 1) share codes in CRSP to be 10 or 11, 2) traded prices to be 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 the total daily trading volume in CRSP. We also exclude regulated firms in the financial and utilities industries (Standard Industry Classification (SIC) codes between 6000 and 6999 and between 4900 and 4999). We obtain institutional ownership data from Thomson Reuters' institutional holdings (13F) database, board independence data from BoardEx, and analyst forecasts data from I/B/E/S. In our study, we focus on the purchase transactions, so we drop the sales transactions, and winsorize all continuous variables at 1% and 99%. These restrictions result in a final sample of 166,555 purchase transactions made by 3,599 unique firms.

Variable definition

Technology-linked return (Techret)

[7] A valid transaction is one without a cleanse code of "A" or "S." Open market purchase transactions are those with a transaction code of "P" but without an option sell indicator of "A" or "P". Transactions with the amendment are those with an amendment indicator of "A" in Thomson Financial IDF database.

We use *technology-linked return* of Lee et al. (2019) as the proxy for the friction of knowledge spillover. We download the patent data provided by Kogan et al. (2017). Kogan et al. (2017) extract the relevant information about patents based on the textual analysis. Specifically, we use the firm identifier and technology class from Kogan et al. (2017)[8]. Following Lee et al. (2019), we choose the grant date as the effective date to avoid the look-ahead bias, and use the patents if the matched firms are traded in the common shares (CRSP share codes 10 and 11), non-financial firms (four-digit SIC 6000-6999), non-missing book equity, and non-penny stocks (higher than one dollar). We estimate the technology-linked returns in two steps.

First, following Jaffe (1986) and Bloom et al. (2013), we estimate the pairwise technology closeness ($Tech_{ijt}$), the uncentered correlation of the 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 $T_{it} = (T_{it1}, T_{it2}, \cdots, T_{it678})$ is a vector of firm *i*'s proportional share of patents across 678 cooperative patent classifications (CPC) over the rolling past five years as of time *t*.[9] Technology closeness is between zero and one, and is symmetric. We note that CPC is a patent classification system, jointly developed by the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO), and it has been used since 2013. According to USPTO patent classifications, Lee et al. (2019) use 427 major classes to estimate the technology closeness upto

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[8] We use Match_patent_permco_permno_2022.csv and Match_patent_cpc_2022.csv for firm identifier and technology class, respectively.

[9] We estimate the proportional share of patent in two steps. First, we assign one to the corresponding CPC for each patent. Otherwise, we assign zeros. Each patent may have multiple technology classifications. In this case, we assign one to those multiple corresponding classifications. Second, every five years, we aggregate all numbers, and divide the numbers by the aggregation for each firm. See the details in Lee et al. (2019).

2010. Since our sample period is upto 2017[10], we estimate the technology closedness based on CPC. Different from USPTO classification, CPC has wider categories (about 250,000). Each classification term consists of a symbol such as "A01B33/00", which is tilling implements with rotary driven tools. The first letter consists of one digit, and indicates the section. The second and third letters consists of two digits, and indicate the major class. The fourth letter consists of one digit, and indicate subclass. The rest digits vary from three or more, and indicate group and subgroup. Consistent with Lee et al. (2019), we use the subclass because the number of subclasses in CPC (678) is quite consistent with those under USPTO classification (427). However, our results are robust when we use the major classes in CPC, which is 133.

Second, we compute the technology-linked return (*Techret*) as the average monthly returns of technology-linked firms in the technology space, weighted by technology closeness, as follows,

$$Techret_{it} = \frac{\sum_{j \neq i} Tech_{ijt} * Ret_{jt}}{\sum_{j \neq i} Tech_{ijt}}$$

where Ret_{jt} is the raw return of firm *j* at month *t*. $Tech_{ijt}$ is estimated at the end of calendar year, *y*, based on the grant date, and is matched to the return data from July of year *y*+1 to June of year *y*+2. That is, $techret_{it}$ estimate the portfolio returns of peer firms which have the similar technology of a focal firm *i*. We assume that insiders engage the inside transactions after they observe the technology-linked returns so we match the inside transactions in next month of *Techret*.

Trading Profitability of Insiders

[10] We can estimate *Techret* until 2020. However, the number of observations is very small. For example, # in 2018, # in 2019, and # in 2020. So, we drop the observations. The results do not change by extending our sample upto 2020.

We measure the trading profitability of insiders by estimating abnormal returns over the 180 calendar days after the transaction date. We choose the 180-day estimation period to be consistent with Rule 16(b) of the Securities Exchange Act of 1934 (namely, short-swing rule) that requires all insiders to return profits earned from their trading during a given six-month period to the firm, which is likely to force them not to reverse their position 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*. *Carhart* is the intercept from the Carhart (1997) four-factor model estimated over the 180 calendar days after each trade in percentage. *BHR* is calculated by subtracting the compounded market return, using the CRSP value-weighted index, from the compounded return of each firm over 180 calendar days following the transaction date. We require that the number of trading days is more than 120.

Summary

Table 1 presents the distribution of purchase transactions against technology momentum in each year across different industries. The purchase transactions against technology momentum are 34,222, which is 20% of all purchase transactions (166,555). The insiders' purchase against technology momentum varies over time and across industries. It has increased from 282 in 2001 to 8,293 in 2005, and decreased to 98 in 2017. It is the highest in 2005 (8,293 trades), followed by 2004 (6,935) and 2008 (4,362). Across industries, the number of purchase transactions is mainly executed in manufacturing industries (17,450), followed by service industries (14,996). Overall, Table 1 shows that the purchase transactions driven by technology-linked peer firms have been widely executed over time and across industry.

Panel A of Table 2 reports trading profitability of insiders' purchases exploiting *techret* (*Techret trading*) and their other purchases (*Other trading*), and provides the univariate tests comparing trading profitability of *Techret trading* to *Other trading*. We find that both trading profits and trading volume of *Techret trading* is higher than those of *Other trading*. Carhart alpha (BHR) from *Techret trading* is 0.030% (0.080%) while that from *Other trading* is 0.026% (0.057%). The difference is 0.004% (0.023%), and statistically significant. *Trading volume* from *Techret trading* is 0.002% higher than that of *Other trading* and the difference is significant at 1% level. Overall, these results show that insiders earn higher trading profits and purchase their shares with larger volume by exploiting *techret*.

Panel B provides summary statistics of all variables in our study. Appendix provides a detailed description of the variables. The mean value of *Carhart* and *BHR* have 2.71% and 6.11%, suggesting that insiders earn trading profits from their purchase. Insiders, on average, purchase 0.033% of total share outstanding in each transaction.

Empirical specification

To testify Hypothesis 1 on the friction of knowledge spillover and insider profitability, we specify a regression model at transaction level as follows,

$$Profitability = \alpha + \beta_{Techret}Techret + \beta_{\vec{X}}\vec{X} + \beta_{FE}Fixed\ effects + \varepsilon \tag{1}$$

Profitability is either *Carhart* or *BHR* for each transaction. The main independent variable is *Techret*, the past portfolio returns of technology-linked peer firms. Consistent with our main hypothesis, we expect that $\beta_{Techret}$ is significantly positive.

$\vec{X}$ is the vector of control variables. Following Lakonishok and Lee (2001), we include firm size (*Ln(size)*), market-to-book ratio (*MB*), and *Past returns* because these variables are the important return determinants (e.g., Banz, 1981; Fama and French, 1993; Jegadeesh and Titman, 1993). We control for *ROE* because a firm’s profitability is important determinants of the inside transactions (Huddart, Ke, and Petroni, 2003). Further, we include *Age*, *Leverage*, R&D intensity (*R&D/sale*), *Idiosyncratic volatility*, and *Institutional ownership* to capture the effect of information asymmetry and investment opportunity on the inside trading (Aboody and Lev, 2002; 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 the B*lackout period* (an indicator equal to one if insiders trade during the blackout period, and zero otherwise) because it curbs the inside transactions (Bettis, Coles, and Lemmon, 2000). Lastly, we add firm and transaction date fixed effects to control for the unobserved cross-sectional and time-series variations, and cluster standard errors at transaction date.

To address the endogeneity concerns, we compare the profitability of insider trading before and after their *tech peers* are highly affected by the 2008 FC ruling, following Suh (2023). The property right to a patent between employees and their firm is arranged by a preinvention assignment agreement as a part of employment contract. From the late 1970s to the early 1980s, eight states including California, Delaware, Illinois, Kansas, Minnesota, North Carolina, Utah, and Washington enacted state legislation to protect employees from employer's abuse of superior negotiation on employee inventions. In 2008, the Federal Circuit made the decision[11] which shifted property rights from employees to firms, resulting in favoring firms toward invention assignment agreement in those eight states. Suh (2023) uses the 2008 FC ruling as exogenous shock, and finds that firms headquartered in those eight states increase credits and innovation activities (e.g., patents) after the 2008 FC ruling.

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

Since the exogenous shock affects innovation by *tech peers* in those eight states, we estimate the treatment index (*Treatment index*) in two steps. First, for each a focal firm, we identify headquarters of *tech peers* which issue the patent by using 10-X Header data (Loughran and McDonald, 2016).[12][13] Second, we make the indicator variable by assigning 1 if a technology-linked peer firm is headquartered in one of the eight states, or 0 otherwise. Then, we estimate the average of the indicator for each a focal firm. The higher *Treatment index* for a focal firm, the more innovation by *tech peers* from the eight states. Empirically, we estimate a regression as follows,

$$\begin{aligned} Profitability = {} & \alpha + \beta_{Techret} Techret + \beta_{TI} Treatment\ index\ (TI) \\ & + \beta_{Post} Post3years + \beta_{Techret*TI} Techret * TI \\ & + \beta_{Post*Techret} Post3years * Techret + \beta_{Post*TI} Post3years * TI \\ & + \beta_{Post*Techret*TI} Post3years * Techret * TI + \beta_{\vec{X}} \vec{X} \\ & + \beta_{FE} Fixed\ effects + \varepsilon \end{aligned} \tag{2}$$

To leverage the exogenous shock in 2008, we restrict our sample period 3 years before and after 2008. We use the indicator variables, *Post3years*, equals to 1 if the transaction is executed 3 years after 2008. For the robustness, we estimate the parallel trend over 3 years after the 2008 FC ruling as well. We expect that the post triple interaction term, $\beta_{Post*Techret*TI}$, is significantly positive.

Next, to examine the economic mechanism, we do the cross-sectional analysis. First, we investigate the spillover channel of *tech peers* using their trade secrecy and geographic proximity.

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

[13] We use 10-X Header data because it allows us to have historical headquarter information. Because of the data availability, the final sample period ends in 2018.

If *tech peers* rely on the trade secrecy, the knowledge spillover is restricted, and so the profitability is. Empirically, we estimate the trade secrecy of technology-linked peer firms (*Trade secrecy of tech. peers*) in two steps. First, we download the disclosure-based trade secrecy measure of Glaeser (2018) from the author's website. He identifies "trade secrecy" or "trade secret" from 10-K filings on SEC's EDGAR database, and make the indicator variable (*Trade secrecy*), which equals one if a firm discloses the words in each year, and zero otherwise. Second, similar to Tseng (2022), we estimate the technology-weighted trade secrecy of technology-linked peer firms (*Trade secrecy of tech. peers)* by replacing past returns of peer firms with the trade secrecy indicator. Then, we interact *Techret* with *Trade secrecy of tech. peers*. We further add trade secrecy of a focal firm (*Trade secrecy*). We expect that the interaction term is significantly negative. Moreover, Jaffe, Trajtenberg, and Henderson (1993) find that knowledge spillover is geographically localized. In the similar manner, we estimate the average distance between a focal firm and peer firms (*Log (distance to tech. peers)*), and the interaction term between *Techret* and *Log (distance to tech. peers)*is significantly negative.

Second, we explore how insiders in focal firms exploit the abnormal profit. We rely on the demographic information of insiders: *Ivy league*, and *Industry expertise* indicators, and its interaction term with *Techret* in equation (1). Since the literature documents that the social ties (e.g., education) facilitate the information dissemination, we expect that the interaction term between *Ivy league* and *Techret* is significantly positive. Turning to the industry expertise, the knowledge spillover is stronger in the same technology space than the product market space. This suggests that the industry expertise is not informative for insiders to exploit the friction. We expect that the interaction term between *Industry expertise* and *Techret* is insignificant. Lastly, knowledge is capitalized, and it allows insiders to access the knowledge spillover earlier than others. We estimate the interaction term between knowledge capital (Log(*K_rd)*) and *Techret*, and it is significantly positive.

To examine the effect of trading environment, we use four information asymmetry variables: *Ln(size)*, *Idiosyncratic volatility*, *Analyst dispersion*, and *Bid-Ask spread*. We interact *Techret* with each of information asymmetry variables, and expect that the interaction terms are significantly negative for firm size, and positive for the rest. Also, we examine the effect of legal risk by interacting *Techret* with two legal risk variables from Kim and Skinner (2012) and Huang et al. (2019). We expect the interaction terms are significantly negative.

To testify Hypothesis 2, we estimate the regression model as follows,

$$Trading\ volume = \alpha + \beta_{Techret}Techret + \beta_{\vec{X}}\vec{X} + \beta_{FE}Fixed\ effects + \varepsilon \tag{3}$$

Trading volume is the dollar value of purchase transaction (price*shares) divided by market capitalization. We also replace *Trading volume* to *Opportunistic* (*routine*) *trading volume*, which is *Trading volume* executed by opportunistic (routine) traders. Other control variables are same as equation (1). We expect that the coefficient of *Techret* is significantly positive to all trading volume measures, not *routine trading volume*.

Next, we explore how the insider trading increases the knowledge dissemination in the stock market. While *Techret* predicts future stock return (Lee at al., 2019), its predictability becomes weak if insider trading delivers the proprietary information in the market. We estimate Fama-MacBeth regression as follows,

$$\begin{aligned} Return = \alpha + \beta_{Techret}Techret + \beta_{Purchase}Purchase \\ + \beta_{Techret*Purchase}Techret * Purchase + \beta_{\vec{X}}\vec{X} + \varepsilon \end{aligned} \tag{4}$$

where *Return* is the one-month future excess stock return, and $Purchase$ is the indicator variable, equals to 1 if insiders execute the transactions against technology momentum in the following month of *Techret*, and 0 otherwise. $\vec{X}$ includes firm size, book-to-market ratio, past returns from month *t*-2 to month *t*-13, past returns in month *t*-1, asset growth, and gross profitability. We expect that $\beta_{Techret}$ is significantly positive and more importantly, $\beta_{Techret*Purchase}$ is significantly negative.

Lastly, we investigate Hypothesis 4. Predictability of *Techret* suggests that the proprietary information is not yet revealed. If so, firms with high *Techret* try to curb the knowledge dissemination by increasing trade secrecy and reducing patent disclosure. However, the insider trading breaks the tension between the knowledge spillover and the proprietary cost by revealing the proprietary information. Then, firms with high *Techret* less rely on the trade secrecy and increases the patent filing because the patent grant the legal protection.

$$\begin{aligned} Innovation\ disclosure \\ &= \alpha + \beta_{Techretsum} Techret_{sum} + \beta_{AnnualPurchase} Annual\ Purchase \\ &+ \beta_{Techretsum*AnnualPurchase} Techret_{sum} * Annual\ Purchase \\ &+ \beta_{\vec{X}} \vec{X} + \varepsilon \end{aligned} \tag{5}$$

Innovation disclosure is either *Trade secrecy*, *Patent filing*, and *Patent value*. Because *Techret* is at monthly frequency, we annualize it. $Techret_{sum}$ is the sum of technology-linked returns for firm *i* in year *t*. *Annual Purchase* is the indicator variable, equals to 1 if insiders execute the transactions following month of *Techret* in year *t*, and 0 otherwise. For *Trade secrecy*, we estimate the probit regression with the industry and year fixed effects, following Glaeser (2018). For *Patent filing* and *Patent value*, we use the panel regression with the firm and year fixed effects. For both models, we use *size*, *BM*, *Past return*, *Total volatility*, *Leverage*, *ROA*, *R&D expenditure*, *Loss* (indicator), *R&D* (indicator), *Special/Assets*, *and Institutional ownership,* similar to Glaeser (2018). The standard errors are estimated at firm level. We expect that $\beta_{Techretsum}$ is positive for *Trade secrecy* while it is negative for *Patent filing*, and *Patent value*. More importantly, $\beta_{Techretsum*AnnualPurchase}$ is negative for *Trade secrecy* while it is positive for *Patent filing*, and *Patent value*.

4. Main Results: Insider Profitability

Basement finding

Table 3 presents the regression results of the insider trading profitability on the past returns of technology-linked peer firms (*Techret*). In column (1), we find that the coefficient on *Techret* is positive and significant at the 1% level. The coefficient of 0.385 for *Techret* suggest that a one-standard-deviation increase in this variable is associated with a 1.89% increase in *Carhart* over 180 days. In column (2), we replace *Carhart* with *BHR*. Similar to *Carhart*, the magnitude of *Techret* is significantly positive at 1% significance level. Overall, when the portfolio return of technology-linked peer firms increases, insiders purchase their shares, and their profitability is significant and positive. This is consistent with the prediction of our main hypothesis (Hypothesis 1) where insiders leverage the information of new innovation by peers earlier than outside investors in the stock market.

For the completeness, we estimate the main regression by changing the model specifications. Column (3) and (4) use both firm and year fixed effects. Column (5) and (6) use industry fixed effect to control for the industry-wise variation (e.g., product market competitions) over time. Column (7) and (8) use firm- -year fixed effect to control for the time-varying firm-level variations over time. Regardless of different fixed effects, we find the similar results.

Addressing the endogeneity

We estimate the model (2) in Table 4. To save space, we show the main interaction terms.[14] In columns (1) and (2), we find that the coefficient of the triple interaction term between *Techret*, treatment index, and post 3 years ($\beta_{Post*Techret*TI}$) is significantly positive. This means after the 2008 FC ruling passed, insiders make the significant profits using the knowledge spillover from innovation by *tech peers* whose headquarters are located in the eight states. In columns (3) and (4), we estimate the pararell trends, and find that insiders make the profitability 2 and 3 years after the 2008 FC ruling.

Economic channel: Technology peers

To understand how the knowledge dissemination drives the inside transaction, we estimate the abnormal profits across *tech peers*' trade secrecy and geographic proximity in Table 5. Trade secrecy discourages firms to disclosure information on their technology, and the trade secrecy of technology-linked firms lowers the effect of knowledge spillover on stock market (Tseng, 2022). We interact *Trade secrecy of tech. peers* with *Techret*, and present the results in Column (1) and (2) in Table 5.

We find that *Techret* still significantly predicts insiders' abnormal profits using both *Carhart* and *BHR*. However, the interaction term is significantly negative. For example, the coefficient of the interaction term in Column (1) is -1.943, and it is significant at 1% level. This suggests that the insiders' trading profitability decreases when their peer firms disclose trade secrecy, especially those in the same technology space.

[14] The full version of Table 4 is available upon request.

Turning to the local peers, we estimate the average distance between a focal firm's headquarter and tech peers' headquarters and take a logarithm value of the average distance (*log (distance to tech. peers)*). In Column (3) and (4), we find that the interaction terms are significantly negative. This is consistent with Jaffe, Trajtenberg, and Henderson (1993) where the knowledge spillover is localized.

Economic channel: Insider's information set

Even though the knowledge spillover comes from *tech peers*, not all insiders can exploit the friction. In this subsection, we explore how insiders process the knowledge spillover. First, we investigate whether insiders access to the knowledge spillover through their education background, *Ivy leagues*. Graduating from top schools refers to individuals' ability to analyze investment issues with greater precision, as well as their strong education ties, which enable them to gather superior information about the firm, and thus those with a strong education background earn higher returns on their investments (Cohen, Frazzini, and Malloy, 2010; King, Srivastav, and Williams, 2016). Aligned with these findings, we expect that insiders with a strong education background are better able to exploit the friction from the knowledge spillover and earn larger profits than those without. In Columns (1) and (2) of Table 6, we find that the interaction terms between *Ivy league* and *Techret* are 1.670 and 2.222 and significant at 1% level, respectively.

Second, as an intangible asset, innovation requires the comprehensive understanding. Since knowledge can be capitalized, we expect that if insiders work at firms with more knowledge capital, they understand the knowledge spillover earlier than others. We estimate the knowledge capital using the inventory method, and estimate the interaction term between knowledge capital and *Techret* in Columns (3) and (4). We find that the interaction term is significantly positive.

Lastly, we investigate whether the industry expertise helps to process the knowledge spillover. However, we find that the coefficients of interaction term between *Industry expertise* and *Techret* are insignificant in Columns (5) and (6). This reveals that experts in one industry cannot make the abnormal profits by using technology-related news. This echoes the finding of Bloom et al. (2013) where they show that knowledge spillover appears in the same technology space not in the same product space.

Trading environment: Information asymmetry & Legal risk

Information asymmetry influences insiders' incentives and ability to engage the profitable transactions (Aboody and Lev, 2002; Huddart and Ke, 2007). Also, Lee et al. (2019) find that technology momentum exists from investor's inattention, generating the lagged stock price reaction to knowledge spillover. We estimate the interaction term with four information asymmetry variables, including firm size (*ln(Size)*), idiosyncratic volatility (*Ivol*), *Analyst dispersion*, and *Bd-Ask spread*, in Panels A and B of Table 7. We find that the insider profit is higher when the information asymmetry is higher across different measures.

Also, we examine whether a firm's legal risk affects the profitability. Prior studies show that insiders do not trade their sales to avoid the legal risk (Cheng and Lo, 2006; Rogers, 2008). We use two legal risk measures: *probability of being sued* (Kim and Skinner, 2012)[15], and *judge ideology* (Huang et al.,2019)[16]. We then interact each of legal risk variables with *Techret* in Panel C. We find that all interaction terms are significantly negative.

Robustness check

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[15] We estimate the litigation risk by extrapolating the model (3) of Table 7 in Kim and Skinner (2012).

[16] Huang et al. (2019) provide the new measure of litigation risk by using the federal judge ideology based on the fact that firms in liberal courts are more likely to be sued in securities class action lawsuits than in conservative circuits. We thank to the authors for providing us the data.

We use the alternative specifications for the robustness. First, we measure *Techret* by replacing past one-month lagged returns of *tech peers* with six- or twelves-month lagged returns of *tech peers* (*techret6*, and *techret12*, respectively). Considering that return predictability of *Techret* is persistence (Lee et al., 2019), we expect that insiders utilize *Techret* not only in the recent month but also in earlier periods, and earn abnormal profits. Panel A of Table 8 presents the regression results. We find that the coefficients of *techret6* and *techret12* are significantly positive. The results suggest that the information friction of knowledge spillover is persistent over one year.

Second, we change the trading specification. We relax the time gap between insiders' transaction date and *Techret* from one month to three months. In Column (1) and (2) of Panel B, we find that insiders earn profits from transactions over next three-months of *Techret*. Next, we estimate *Techret* by using different class system; patent major classes (*Techret_major)*. We measure *Techret_major* by using 133 major classes, and estimate the regression in Columns (3) and (4). We find that *Techret_major* is significant and positive.

Third, we aggregate the inside transactions into either firm-insider-transaction date or firm-transaction date level to address the potential bias about the cross-sectional dependence when different insiders in the same firm simultaneously trade multiple times. We aggregate both purchase and sales transactions in each firm-insider-transaction date (or firm-transaction date), and retain the observations if the number of purchase transactions is larger than that of sales transactions. We find that the insiders make the significantly positive profits in Panel C.

5. Trading volume and opportunistic trading

High proprietary cost prevents the insider trading to restrict the knowledge dissemination (Choi et al., 2024). However, we hypothesize that insiders trade their shares more if the friction of knowledge spillover exists. We estimate the model (3) in Table 9.

First, in Column (1), we find that the coefficient on *Techret* is positive and significant, consistent with Hypothesis 2. The coefficients of 0.039 for *Techret* indicate that insiders increase trading volume by 0.11% when *Techret* increases by one standard deviation.

Second, we classify insiders into opportunistic insiders and routine insiders, and examine whether opportunistic insiders increase their trading volume. Following Cohen et al. (2012) and Massa et al. (2015), we identify opportunistic insiders and routine insiders based on their past trading activity, and make *Opportunistic trading volume* (*Routine trading volume*) as the dollar value of opportunistic (routine) insiders' purchase transaction divided by market capitalization. In Column (3) where we use *Opportunistic trading volume* as our dependent variable, we find that the coefficient of *Techret* is positive and significant. While *Techret* is significant in Column (4) where we replace *Opportunistic trading volume* to *Routine trading volume*, the coefficient is 10 times smaller than that in Column (3).

For the robustness, we replace *Techret* with *Techret_major*, and estimate the regressions in Column (2), (5), and (6). Similarly, we find that *Techret_major* increases the trading volume, and *Opportunistic trading volume* is much larger than *Routine trading volume*.

6. Market efficiency: Insider purchase and return predictability of *Techret*

So far, we find that insiders exploit the friction about knowledge spillover. Because the insider trading conveys the proprietary information to the stock market, we investigate whether their trading reduces the friction. We estimate the model (4) in Table 10. We make the indicator variable, *Purchase*$_t$ *(indicator)*, which equals to 1 if insiders engage in purchase transactions in month t following *Techret* in month t-1, and 0 otherwise and then, we estimate Fama-MacBeth regressions of *Purchase*$_t$ *(indicator)* on the excess return in month t.

First, we note that *Purchase*$_t$ *(indicator)* is contemporary trades, executed in the same month of predicted return because we assume that insiders trade stocks in the following month after they observe *Techret* and these transactions weaken the return predictability of *Techret*. In Column (1), we find that the coefficient of *Techret* is positive and significant at the 5% level, suggesting that *Techret* significantly predicts the future return. In Column (2), we add the interaction term between *Purchase*$_t$ *(indicator)* and *Techret*, and find that the coefficient on the interaction term is significantly negative, while the coefficient on *Techret* remains significantly positive. This indicates that the information of *Techret* is reflected in the stock price simultaneously when insiders execute the transactions. The results are robust when we control for more variables in Column (3).

Second, we construct *Opportunistic Purchase*$_t$ *(indicator)*, which equals to 1 if insiders engage the opportunistic (routine) transactions in month t following *Techret* in month t-1, and 0 otherwise. We similarly replace *Purchase*$_t$ *(indicator)* to *Opportunistic Purchase*$_t$ *(indicator)*, estimate the regression, and report the results in Columns (4) and (5). We find that the coefficient on the interaction term between *Opportunistic Purchase*$_t$ *(indicator)* and *Techret* is significantly negative.

Lastly, we examine whether insiders purchase transactions following *Techret* itself predicts future stock return since the trades include the technology-related fundamental information about their peers. We make the indicator variable, *Purchase*$_{t-1}$ *(indicator)*, which equals to one if insiders engage in purchase transactions in month t-1 following *Techret* in month t-2, and zero otherwise. In Column (7), we confirm that *Purchase*$_{t-1}$ *(indicator)* is significantly positive on the excess return in month t. When insiders execute the transactions following *Techret*, future stock returns increase by 1% per month. The results are robust when we add control variables in Column (8).

Overall, we close this section by concluding that insider trading increases the market efficiency by lowering the return predictability of *Techret*. That is, the insider trading reduces the information friction and enhances the dissemination speed of knowledge spillover.

7. Insider trading, proprietary cost, and disclosure policy

Higher *Techret* indicates that more knowledge spillover will be slowly disseminated with higher the proprietary cost. Firms with high *Techret* increases the trade secrecy and restrict the patent activity to limit the knowledge spillover. However, if insiders exploit the friction, the proprietary information is revealed on time, then firms with high *Techret* decreases the trade secrecy and increases the patent activity to have the legal protection. We estimate the model (5) in Table 11.

First, we find that the coefficient of $Techret_{sum}$ is significantly positive on trade secrecy in Column (1). However, the coefficients are significantly negative on both patent filing and patent quality in Columns (3) and (5), respectively. This suggests that when the knowledge spillover is sluggish, firms rely on the trade secrecy to lower proprietary cost.

Second, we interact *Annual Purchase* with $Techret_{sum}$, and estimate how the insider trading changes the disclosure decisions. In Column (2), the interaction term is significantly negative on trade secrecy. Also, in Column (4) and (6), the interaction terms are positive on the patent filing and quality. This is consistent with Hypothesis 4. That said, as the insider trading expedite the dissemination of proprietary information and cost in the stock market, managers engage more patent activities to protect their knowledge and less rely on trade secrecy. These results show that the insider trading affects the strategic innovation disclosure by spurring the knowledge spillover.

8. Conclusion

Knowledge spillover is reluctant to spurred due to the information frictions, driven by technology proximity and proprietary cost. The frictions generate the slow dissemination of knowledge spillover, and the past returns of technology-linked peer firms (*Techret*) captures the friction by predicting future returns of focal firms. In this study, we investigate whether insiders exploit the friction of knowledge dissemination in their trades since they have the information advantage over the frictions.

We find that they make the abnormal profits, and their profits are larger if *tech peers* less rely on trade secrecy, if *tech peers* are closely located to focal firms, if insiders have the elite education ties, and if insiders understand the knowledge capital. *Techret* increases the insider trading volume, particularly opportunistic trading as well.

Also, we examine how the insider trading affects the tension between knowledge spillover and proprietary cost under the friction. First, the purchase trade following *Techret* lowers the return predictability of *Techret*. Further, it predicts future stock returns. These confirm that the insider transactions enhance the dissemination speed of knowledge spillover. Second, the purchase following *Techret* changes the strategic disclosure policies by increasing the patent activity and decreasing the trade secrecy. Overall, our findings shed light on the inside trading exploiting the friction of knowledge spillover shapes the proprietary costs, and the corporate innovation disclosure.

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Table 1
Distribution of purchase transactions against technology momentum 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
2001	6 (1.00)	15 (0.13)	167 (0.20)	3 (0.04)	47 (0.14)	44 (0.09)	0 (0.00)	282 (0.15)
2002	8 (1.00)	46 (0.31)	850 (0.48)	8 (0.03)	32 (0.04)	102 (0.07)	0 (0.00)	1,046 (0.24)
2003	0 (0.00)	16 (0.13)	375 (0.26)	14 (0.05)	45 (0.19)	66 (0.02)	0 (0.00)	516 (0.10)
2004	4 (0.27)	73 (0.24)	1,094 (0.32)	12 (0.01)	181 (0.15)	5,571 (0.81)	0 (0.00)	6,935 (0.52)
2005	8 (0.16)	50 (0.06)	2,007 (0.42)	42 (0.02)	135 (0.08)	6,051 (0.78)	0 (0.00)	8,293 (0.48)
2006	0 (0.00)	4 (0.00)	1,778 (0.26)	26 (0.02)	40 (0.04)	850 (0.32)	0 (0.00)	2,698 (0.18)
2007	2 (0.33)	40 (0.03)	2,251 (0.28)	89 (0.07)	72 (0.06)	293 (0.09)	0 (0.00)	2,747 (0.18)
2008	1 (0.03)	87 (0.02)	3,338 (0.21)	43 (0.01)	91 (0.02)	802 (0.16)	0 (0.00)	4,362 (0.14)
2009	11 (0.52)	12 (0.02)	1,561 (0.30)	28 (0.06)	22 (0.03)	156 (0.07)	0 (0.00)	1,790 (0.19)
2010	3 (0.60)	8 (0.02)	663 (0.18)	16 (0.06)	7 (0.01)	247 (0.21)	0 (0.00)	944 (0.15)
2011	7 (0.70)	13 (0.02)	771 (0.16)	20 (0.02)	17 (0.02)	79 (0.05)	0 (0.00)	907 (0.10)
2012	0 (0.00)	17 (0.03)	1,069 (0.19)	12 (0.01)	24 (0.04)	129 (0.08)	0 (0.00)	1,251 (0.12)
2013	1 (0.04)	34 (0.08)	489 (0.13)	7 (0.03)	29 (0.07)	178 (0.15)	0 (0.00)	738 (0.12)

2014	0	14	248	13	12	158	0	445
	(0.00)	(0.03)	(0.06)	(0.06)	(0.02)	(0.13)	(0.00)	(0.07)
2015	0	28	546	20	74	147	0	815
	(0.00)	(0.04)	(0.16)	(0.06)	(0.08)	(0.05)	(0.00)	(0.10)
2016	1	4	170	10	57	113	0	355
	(0.02)	(0.01)	(0.04)	(0.04)	(0.08)	(0.05)	(0.00)	(0.05)
2017	1	5	73	0	9	10	0	98
	(0.01)	(0.02)	(0.07)	(0.00)	(0.03)	(0.01)	(0.00)	(0.03)
Total	53	466	17,450	363	894	14,996	0	34,222
	(0.03)	(0.03)	(0.22)	(0.03)	(0.05)	(0.33)	(0.00)	(0.20)

This table presents the distribution of the number of purchase transactions against technology momentum by year and industry. We define purchase transactions against technology momentum as insiders' purchases executed following technology momentum, measured by the past returns of technology-linked peers. The sample consists of 34,222 purchase transactions driven by technology momentum among total 166,555 purchase transactions from 2001 to 2017. The numbers in brackets are the percentages of the number of purchase transactions against technology momentum over the number of total purchase transactions in each year and industry.

Table 2
Summary statistics

Panel A. Univariate tests

	Techret trading			*Other trading*			Difference		
	Mean	STD	N	Mean	STD	N	Mean	STD	P-Value
Carhart	0.030	0.002	34,222	0.026	0.001	135,910	0.004	0.002	0.037**
BHR	0.080	0.003	34,222	0.057	0.001	135,910	0.023	0.002	0.000***
Trading volume	0.028	0.000	34,222	0.026	0.000	135,910	0.002	0.000	0.000***

Panel B. Descriptive statistics

Variables	Mean	STD	P10	P25	Median	P75	P90	N
Techret	-0.0010	0.0273	-0.0020	0.0000	0.0000	0.0000	0.0007	166,555
Carhart	0.0271	0.2898	-0.3224	-0.1209	0.0275	0.1844	0.3668	166,555
BHR	0.0611	0.3899	-0.3451	-0.1769	-0.0020	0.2193	0.5303	166,555
Trading volume	0.0336	0.1830	0.0003	0.0010	0.0038	0.0168	0.0630	166,555
Ln(Size)	2064.8	5181.2	54.2	125.4	424.9	1657.8	4557.4	166,555
MB	3.5198	4.7795	0.6812	1.1841	2.1425	4.2763	7.1474	166,555
Past return	0.0028	0.4415	-0.3993	-0.2558	-0.0838	0.1142	0.4433	166,555
ROE	-0.1068	0.4668	-0.5216	-0.1305	0.0331	0.1078	0.1965	166,555
Age	18.1522	15.0817	4.0000	8.0000	13.0000	23.0000	42.0000	166,555
Leverage	0.4689	0.2126	0.1988	0.3028	0.4635	0.6207	0.7741	166,555
R&D/Sales	0.3602	1.4869	0.0000	0.0000	0.0067	0.1586	0.4057	166,555
Idiosyncratic volatility	0.0285	0.0127	0.0143	0.0196	0.0257	0.0345	0.0443	166,555
Institutional ownership	0.5490	0.3150	0.0939	0.2801	0.5516	0.7994	0.9596	166,555
Board independence	0.8177	0.1096	0.6667	0.7500	0.8571	0.8889	0.9167	166,555
Equity ownership by each insider	0.1280	0.1702	0.0002	0.0016	0.0495	0.1801	0.3897	166,555
Transaction size	0.0018	0.0034	0.0000	0.0001	0.0005	0.0017	0.0047	166,555
Blackout period	0.5809	0.4934	0.0000	0.0000	1.0000	1.0000	1.0000	166,555
Analyst dispersion	0.0137	0.0331	0.0004	0.0009	0.0025	0.0081	0.0272	116,319
Bid-Ask spread	0.0062	0.0136	0.0005	0.0010	0.0021	0.0059	0.0144	163,509

Panel A of this table presents results from univariate test of trading profitability and trading volume on trading against technology momentum and other trading. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Panel B presents the descriptive statistics of transaction characteristics. The sample period is from 2001 to 2017.

Table 3
Trading profitability of insiders' purchases against technology momentum

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Carhart	BHR	Carhart	BHR	Carhart	BHR	Carhart	BHR
Techret	0.385***	0.558***	0.404***	0.460**	0.448***	0.542***	0.336**	0.406**
	(0.000)	(0.000)	(0.003)	(0.016)	(0.000)	(0.000)	(0.016)	(0.037)
ln(Size)	-0.103***	-0.135***	-0.120***	-0.159***	-0.008***	0.004	-0.140***	-0.190***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.198)	(0.000)	(0.000)
MB	-0.009***	-0.014***	-0.011***	-0.017***	-0.002***	-0.003***	-0.013***	-0.020***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past return	-0.110***	-0.159***	-0.138***	-0.207***	-0.040***	-0.049***	-0.150***	-0.226***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROE	-0.062***	-0.098***	-0.103***	-0.154***	0.014*	-0.007	-0.138***	-0.177***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.067)	(0.513)	(0.000)	(0.000)
Age	-0.043***	-0.045***	-0.078***	-0.082***	0.001	0.005	-0.055***	-0.022
	(0.001)	(0.009)	(0.000)	(0.000)	(0.834)	(0.280)	(0.000)	(0.186)
Leverage	0.260***	0.318***	0.226***	0.308***	0.045***	0.049**	0.234***	0.342***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.030)	(0.000)	(0.000)
R&D/Sales	-0.032***	-0.046***	-0.038***	-0.056***	0.007***	0.001	-0.046***	-0.064***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.727)	(0.000)	(0.000)
Idiosyncratic volatility	1.424***	2.662***	1.909***	3.162***	0.887***	1.835***	1.527***	4.461***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Institutional ownership	0.035	-0.027	0.084***	0.047	0.005	-0.026*	0.125***	0.109**
	(0.112)	(0.385)	(0.003)	(0.248)	(0.615)	(0.059)	(0.000)	(0.018)
Board independence	0.078**	0.084	0.130***	0.127**	-0.045	-0.018	0.225***	0.228***
	(0.032)	(0.108)	(0.001)	(0.024)	(0.126)	(0.705)	(0.000)	(0.001)
Equity ownership by each insider	-0.240***	-0.342***	-0.400***	-0.557***	-0.127***	-0.146***	-0.443***	-0.630***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Transaction size	4.873***	5.028***	6.909***	7.067***	3.152***	2.289*	6.980***	7.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.061)	(0.000)	(0.000)
Blackout period	-0.008	-0.002	0.006	0.027***	-0.016**	-0.005	0.005	0.031***
	(0.273)	(0.772)	(0.231)	(0.000)	(0.036)	(0.581)	(0.352)	(0.000)
Firm fixed effects	Yes	Yes	Yes	Yes				
Industry fixed effect					Yes	Yes		

Date fixed effects	Yes	Yes			Yes	Yes		
Year fixed effect			Yes	Yes				
Firm x Year fixed effects							Yes	Yes
Adjusted R-squared	0.556	0.560	0.422	0.410	0.336	0.349	0.449	0.436
Observations	166,555	166,555	166,577	166,577	166,850	166,850	166,078	166,078

This table presents estimates from ordinary least square (OLS) regressions of the trading profitability on *Techret*. The sample consists of 166,555 insider purchases from 2001 to 2017. The dependent variable in columns (1), (3), (5), and (7) is the alpha from the Carhart (1997) four-factor models estimated over 180 days following the transaction date (*Carhart*) in percentage, and the dependent variable in columns (2), (4), (6), and (8) is the market-adjusted buy-and-hold returns over the 180 days following the transaction date (*BHR*). *Techret* is the past portfolio return of technology-linked peer firms on one month before the transaction month. We define *tech peers* whose technology class is the same as the focal firm using 678 cooperative patent classification (CPC) over the rolling past five years. Appendix provides a detailed description of the variables. *P*-values reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustered at the date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Exogenous shock: the 2008 FC ruling

	(1)	(2)	(3)	(4)
Variables	Carhart	BHR	Carhart	BHR
Techret (a)	1.900***	0.211	1.905***	0.201
	(0.000)	(0.703)	(0.000)	(0.717)
Treatment Index (b)	-0.037	-0.024	-0.036	-0.043
	(0.547)	(0.788)	(0.552)	(0.631)
(a)*(b)	-3.890***	-0.456	-3.886***	-0.406
	(0.000)	(0.716)	(0.000)	(0.746)
Post3years*Techret*Treatment Index	2.973*	4.639*		
	(0.076)	(0.057)		
Year t+1 *Techret*Treatment Index			2.462	3.937
			(0.213)	(0.203)
Year t+2 *Techret*Treatment Index			8.180**	13.449***
			(0.037)	(0.003)
Year t+3*Techret*Treatment Index			4.191*	3.699
			(0.072)	(0.327)
Post3years, Post3years*(a), Post3years*(b)	Yes	Yes		
Year t+1, Year t+1*(a), Year t+1*(b)			Yes	Yes
Year t+2, Year t+2*(a), Year t+2*(b)			Yes	Yes
Year t+3, Year t+3*(a), Year t+3*(b)			Yes	Yes
Controls (same as Table 3)	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.605	0.607	0.605	0.608
Observations	102,293	102,293	102,293	102,293

This table presents estimates from ordinary least square (OLS) regressions of the trading profitability on *Techret* by using the Federal circuit (FC) ruling in 2008 as an exogenous shock. The sample consists of 102,293 insider purchases 3 years before and after 2008. The dependent variable in columns (1), (3), (5), and (7) is *Carhart*, and the dependent variable in columns (2), (4), (6), and (8) is *BHR*. *Treatment Index* is the average of the indicator variable, equals to 1 if the headqurter is located in one of the eight FC state, or 0 otherwise, among technology-linked peer firms. *Post3years* is an indicator variable, equals to 1 if the transaction occurs 3 years after 2008, or 0 otherwise. *Year t+1* (*t+2*, *t+3*) is an indicator variable, equals to 1 if the transaction occurs in 2009 (2010, 2011), or 0 otherwise. Appendix provides a detailed description of the variables. *P*-values reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustered at the date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Effects of knowledge spillover on trading profitability against technology momentum

	(1)	(2)	(3)	(4)
Variables	Carhart	BHR	Carhart	BHR
Techret	1.934***	1.504***	17.355***	15.584***
	(0.000)	(0.001)	(0.000)	(0.001)
Techret*Trade secrecy of tech. peers	-1.943***	-1.185**		
	(0.000)	(0.021)		
Trade secrecy of tech. peers	0.001	0.021		
	(0.957)	(0.500)		
Trade secrecy	0.002	0.003		
	(0.753)	(0.748)		
Techret* Ln (distance to tech. peers)			-2.236***	-1.979***
			(0.000)	(0.002)
Ln (distance to tech. peers)			0.003*	0.005**
			(0.082)	(0.047)
Controls (same as Table 3)	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.556	0.561	0.561	0.566
Observations	166,555	166,555	165,504	165,504

This table presents estimates from ordinary least square (OLS) regressions of the trading profitability on *Techret* depending on tech. peers' trade secrecy and geographic proximity. The sample consists of 166,555 insider purchases from 2001 to 2017. The dependent variable in column (1) is *Carhart*, and the dependent variable in column (2) is *BHR*. *Trade secrecy of tech. peers* is the technology-weighted trade secrecy of technology-linked peer firms. *Trade secrecy* is an indicator that takes the value of one if insiders' firm discloses "trade secrecy" or "trade secret" from 10-K filings on SEC's EDGAR database, and zero otherwise. *Ln (distance to tech. peers)* is the logarithm value of average distance between a focal firm and peer firms. Appendix provides a detailed description 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
Effects of insiders' ability on trading profitability against technology momentum

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Carhart	BHR	Carhart	BHR	Carhart	BHR
Techret	0.071	0.135	-0.601*	-0.326	0.395***	0.560***
	(0.498)	(0.350)	(0.058)	(0.400)	(0.000)	(0.000)
Techret*Ivy League	0.037***	0.033***				
	(0.000)	(0.000)				
Ivy League	1.670***	2.222***				
	(0.000)	(0.000)				
Ln(K_rd)			0.037**	0.058***		
			(0.010)	(0.004)		
Techret*Ln(K_rd)			0.239***	0.214**		
			(0.001)	(0.018)		
Techret*Industry expertise					0.015**	0.013
					(0.018)	(0.131)
Industry expertise					-0.249	-0.070
					(0.255)	(0.840)
Controls (same as Table 3)	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.559	0.563	0.678	0.668	0.556	0.561
Observations	166,555	166,555	60,407	60,407	166,555	166,555

This table presents estimates from ordinary least square (OLS) regressions of the trading profitability on *Techret* depending on insiders' ability. The sample consists of 166,555 insider purchases from 2001 to 2017. The dependent variable in columns (1), (3), and (5) is *Carhart*, and the dependent variable in columns (2), (4), and (6) is *BHR*. *Ivy league* is an indicator that takes the value of one if an insider holds an undergraduate degree from Ivy league schools, and zero otherwise. *Ln(K_rd)* is the knowledge capital using the inventory method, following Peters and Tayler (2017). *Industry expertise* is an indicator that takes the value of one if an insider has expertise as top management of the public firm whose three-digit SIC code is the same as that of the focal firm, and zero otherwise. Appendix provides a detailed description 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
Effects of trading environments on trading profitability against technology momentum

Panel A. Information asymmetry (ln(Size), Idiosyncratic volatility)

	(1)	(2)	(3)	(4)
Variables	Carhart	BHR	Carhart	BHR
Techret	1.113***	2.100***	-0.431**	-0.663***
	(0.000)	(0.000)	(0.014)	(0.003)
Techret*ln(Size)	-0.132***	-0.280***		
	(0.001)	(0.000)		
Techret*Idiosyncratic volatility			24.810***	37.114***
			(0.000)	(0.000)
Controls (same as Table 3)	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.556	0.561	0.556	0.561
Observations	166,555	166,555	166,555	166,555
Panel B. Information asymmetry (Analyst dispersion, Bid-Ask spread)				
Techret	-0.066	-0.099	0.169	0.233
	(0.591)	(0.571)	(0.174)	(0.183)
Techret *Analyst dispersion	17.350***	23.654***		
	(0.000)	(0.000)		
Techret *Bid-Ask spread			29.449***	47.352***
			(0.000)	(0.000)
Analyst dispersion	1.498***	2.145***		
	(0.000)	(0.000)		
Bid-Ask spread			1.502***	1.656***
			(0.000)	(0.000)
Controls (same as Table 3)	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.656	0.676	0.560	0.564
Observations	116,165	116,165	162,451	162,451
Panel C. Legal risk				
Techret	0.361***	0.411**	0.718***	1.054***
	(0.005)	(0.022)	(0.002)	(0.002)
Techret * probability of being sued	-0.099*	-0.195***		
	(0.057)	(0.008)		
probability of being sued	-0.006***	-0.003		
	(0.004)	(0.239)		
Techret *judge ideology			-0.912*	-1.389**
			(0.053)	(0.042)
judge ideology			-0.144***	-0.083*
			(0.000)	(0.089)
Controls (same as Table 3)	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes

Adjusted R2	0.591	0.596	0.568	0.562
Observations	132,819	132,819	155,844	155,844

This table presents estimates from ordinary least square (OLS) regressions of the trading profitability on *Techret* depending on a firm's information asymmetry and legal risk. The sample consists of 166,555 insider purchases from 2001 to 2017. The dependent variable in columns (1), (3), (5), and (7) is *Carhart*, and the dependent variable in columns (2), (4), (6), and (8) is *BHR*. *Analyst dispersion* is standard deviation of analysts' current-fiscal-year annual EPS forecasts divided by the mean monthly price. *Bid-Ask spread* is annual bid-ask spread of daily stock returns during the most recent fiscal year before the transaction. *probability of being sued* is the probability of litigation for the firm-year estimated using the coefficients from the litigation risk model of Kim and Skinner (2012). *judge ideology* is probability that majority judges in the firm's headquartered state is appointed by Democratic president (Huang, Hui, Li, 2019). Appendix provides a detailed description 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
Robustness test: Alternative Model Specifications

Panel A. Alternative measures of *Techret*				
	(1)	(2)	(3)	(4)
Variables	Carhart	BHR	Carhart	BHR
Techret6	0.148***	0.355***		
	(0.001)	(0.000)		
Techret12			0.138***	0.214***
			(0.000)	(0.000)
Controls (same as Table 3)	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.556	0.561	0.557	0.562
Observations	166,555	166,555	166,555	166,555
Panel B. Alternative measures of *Techret*				
	Transaction time t+3		Major CPC Classification	
Techret	0.542***	0.576***		
	(0.000)	(0.000)		
Techret_major			0.336***	0.523***
			(0.002)	(0.000)
Controls (same as Table 3)	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.556	0.560	0.556	0.560
Observations	166,555	166,555	166,555	166,555
Panel C. Aggregated transactions				
	At the Firm-insider-date level		At the Firm-date level	
Techret	0.001	0.164**	0.000	0.135**
	(0.228)	(0.021)	(0.460)	(0.046)
Controls (same as Table 3)	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.361	0.385	0.313	0.333
Observations	68,446	68,446	56,809	56,809

This table presents estimates from ordinary least square (OLS) regressions of the trading profitability on alternative measure of *Techret* or using the aggregated transactions sample. The sample consists of 166,555 insider purchases from 2001 to 2017. The dependent variable in columns (1), (3), (5), and (7) is *Carhart*, and the dependent variable in columns (2), (4), (6), and (8) is *BHR*. *Techret6*, and *Techret12* is the average monthly returns of technology-linked firms in the same technology space, weighted by technology closeness over last 6, and 12 months before each transaction. *Techret_major* is the average monthly returns of technology-linked firms in the same technology space, weighted by technology closeness over 1 month before each transaction, defining technology-linked peer firms based on 133 major classes by CPC. Appendix provides a detailed description 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
Trading volume of Insiders' purchases against technology momentum

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Trading volume		Opportunistic trading volume		Routine trading volume	
Techret	0.039***		0.036***		0.003**	
	(0.005)		(0.008)		(0.017)	
Techret_major		0.064**		0.061*		0.003**
		(0.042)		(0.052)		(0.019)
Controls (same as Table 3)	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.448	0.348	0.446	0.347	0.118	0.086
Observations	166,555	166,555	166,555	166,555	166,555	166,555

This table presents estimates from ordinary least square (OLS) regressions of the trading volume on *Techret*. The sample consists of 166,555 insider purchases from 2001 to 2017. The dependent variable in columns (1) and (2) is the dollar value of purchase transaction divided by market capitalization (*Trading volume)),* and the dependent variable in columns (3) and (4) ((5) and (6)) is the dollar value of opportunistic (routine) insiders' purchase transaction divided by market capitalization (*Opportunistic (Routine) trading volume)*. Appendix provides a detailed description 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 10
Market efficiency and insider trading against technology momentum

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Techret	0.142**	0.141**	0.138**	0.141**	0.139**		
	(0.011)	(0.013)	(0.020)	(0.012)	(0.019)		
$Purchase_t$		-0.004	-0.010				
		(0.734)	(0.527)				
$Purchase_{t-1}$						0.010***	0.008**
						(0.004)	(0.045)
$Tecret*Purchase_t$		-0.484**	-0.845*				
		(0.036)	(0.094)				
Opportunistic $Purchase_t$				-0.003	-0.019		
				(0.779)	(0.312)		
Techret* Opportunistic $Purchase_t$				-0.511**	-0.726		
				(0.048)	(0.162)		
Ln(Size)			0.000		0.000		0.001
			(0.606)		(0.601)		(0.530)
BM			0.006***		0.006***		0.006**
			(0.010)		(0.010)		(0.017)
Past return from t-2 to t-13			-0.004		-0.003		-0.004
			(0.328)		(0.331)		(0.322)
Past return from t-1			-0.021**		-0.021**		-0.020***
			(0.019)		(0.019)		(0.002)
Asset growth			-0.005***		-0.005***		-0.005**
			(0.010)		(0.009)		(0.019)
Gross profitability			0.012***		0.012***		0.012***
			(0.000)		(0.000)		(0.002)
Constant	0.010*	0.011*	-0.003	0.010*	-0.003	0.007	-0.008
	(0.088)	(0.077)	(0.860)	(0.078)	(0.850)	(0.203)	(0.610)
Observations	118,872	118,872	97,056	118,872	97,054	117,481	96,061
Average R^2	0.00863	0.013	0.063	0.0128	0.0629	0.002	0.0544

This table presents estimates from Fama-MacBeth regressions of the following excess monthly return on *Techret*. *$Purchase_t$* (*$Purchase_{t-1}$*) is an indicator that takes the value of one if insiders engage in purchase transactions in month t(t-1) following *Techret* in month t-1(t-2). *Opportunistic $Purchase_t$* is an indicator that takes the value of one if insiders engage in opportunistic purchase transactions after *Techret* exists, and zero otherwise. Appendix provides a detailed description 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 11
Effects of insider trading on the strategic disclosure policies

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Trade secrecy		Patent filing		Patent value	
$Techret_{sum}$	0.123**	0.176**	-0.047**	-0.054**	-0.032*	-0.060***
	(0.044)	(0.011)	(0.025)	(0.036)	(0.079)	(0.003)
Annual Purchase		0.160***		-0.054**		-0.018
		(0.000)		(0.023)		(0.368)
$Techret_{sum}$*Annual Purchase		-0.266**		0.018		0.106**
		(0.025)		(0.736)		(0.016)
Ln(Size)	0.097***	0.096***	0.087***	0.086***	0.031**	0.031**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)	(0.021)
BM	-0.072***	-0.073***	0.040***	0.040***	-0.007	-0.006
	(0.008)	(0.007)	(0.003)	(0.003)	(0.521)	(0.551)
Past returns	0.020	0.020	-0.017**	-0.017**	-0.006	-0.006
	(0.301)	(0.290)	(0.018)	(0.018)	(0.283)	(0.300)
Total volatility	1.988***	2.012***	0.976***	0.976***	0.592***	0.591***
	(0.008)	(0.007)	(0.000)	(0.000)	(0.004)	(0.004)
Leverage	-0.394***	-0.398***	0.003	0.003	-0.006	-0.005
	(0.000)	(0.000)	(0.963)	(0.952)	(0.876)	(0.896)
ROA	-0.207**	-0.220**	0.033	0.035	0.010	0.011
	(0.030)	(0.021)	(0.488)	(0.465)	(0.773)	(0.754)
R&D expenditure	0.697***	0.686***	0.130	0.132	0.107	0.108
	(0.001)	(0.001)	(0.332)	(0.324)	(0.239)	(0.236)
Loss	0.148***	0.144***	0.018	0.018	0.021*	0.022*
	(0.000)	(0.000)	(0.259)	(0.246)	(0.059)	(0.055)
R&D (indicator)	0.583***	0.573***	0.044	0.044	0.031	0.031
	(0.000)	(0.000)	(0.326)	(0.325)	(0.544)	(0.547)
Special/Assets	0.195	0.217	-0.049	-0.051	-0.043	-0.045
	(0.340)	(0.289)	(0.524)	(0.502)	(0.481)	(0.455)
Institutional ownership	0.039	0.029	0.012	0.014	-0.045	-0.045
	(0.591)	(0.692)	(0.829)	(0.807)	(0.209)	(0.215)
Firm fixed effects			Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes				
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.250	0.250				
Adjusted R^2			0.745	0.746	0.670	0.671
Observations	16,688	16,688	16,778	16,778	16,778	16,778

This table presents estimates from ordinary least square (OLS) regressions of strategic disclosure policies on *Techret*$_{sum}$. *Patent filing* is the natural logarithm of one plus the number of patent of firm i in year t. *Patent value* is the natural logarithm of one plus the average value per patent and patent value is defined following Kogan et al. (2017). *Techret*$_{sum}$ is the sum of *Techret* of firm *i* in year *t*. *Annual Purchase* is an indicator that takes the value of one if insiders engage in purchase transactions following *Techret* over year *t*. Appendix provides a detailed description 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 A: Description of variables

Appendix A provide descriptions of all variables used in the tables organized alphabetically within each category.

Variable	Definition
Key independent variables:	
Techret	Average monthly returns of technology-linked firms in the same technology space, weighted by technology closeness on 1 month before each transaction
Techret_major	Average monthly returns of technology-linked firms in the same technology space, weighted by technology closeness on 1 month before each transaction, defining technology-linked peer firms based on 133 major classes by CPC.
Techret_sum	The sum of *Techret* of firm *i* in year *t*.
Techret6 (or 12)	Average monthly returns of technology-linked firms in the same technology space, weighted by technology closeness over the last 6 (or 12) months before each transaction
Firm characteristics:	
Age	Natural logarithm of the number of years since the firm is covered in either CRSP or Compustat
Analyst dispersion	Standard deviation of analysts' current-fiscal-year annual EPS forecasts divided by the mean monthly price
Asset growth	Total asset growth
Bid-Ask spread	Annual bid-ask spread of daily stock returns during the most recent fiscal year before the transaction
Board independence	Ratio of the number of independent directors to the total number of directors on the board
Gross profitability	(Sales – Cost of goods and servies)/ Total asset
Idiosyncratic volatility	Daily idiosyncratic volatility from Fama-French three-factor model over the last year.
Institutional ownership	Ratio of the number of shares held by institutions to the total number of share outstanding in the most recent filings before the transactions
judge ideology	Probability that majority judges in the firm's headquartered state is appointed by Democratic president (Huang, Hui, Li, 2019)
Leverage	Total liabilities/total assets
Ln(distance to tech. peers)	Average of the distance (km) among technology-linked peer firms and a focal firm.
Ln(K_rd)	Natural logarithm of the knowledge capital. We estimate the knowledge capital using the inventory method by following Peters and Taylor (2017) as follows,

	$$K\_rd_{it} = (1 - \delta_{RD}) * K_{rd_{it-1}} + \frac{XRD_{it}}{CPI}$$ Where δ_{RD} is the depreciation rate, XRD is the R&D expenditure, and CPI is the consumer price index. See the detail in Peters and Taylor (2017).
Ln(Size)	Natural logarithm of total assets
Loss	Indicator variable equals to 1 if income before extraordinary item is negative. Otherwise, 0.
MB	Ratio of the market value of equity to the book value of equity.
Past return from t-2 to t-13	Market-adjusted buy-and-hold returns from month $_{t-12}$ to month $_{t-2}$
Past return from t-1	Market-adjusted buy-and-hold returns over month $_{t-1}$
probability of being sued	Probability of litigation for the firm-year estimated using the coefficients from the litigation risk model of Kim and Skinner (2012)
R&D dummy	Indicator variable equals to 1 if R&D expenditure is not missing. Otherwise, 0.
R&D/Assets	R&D expenditure/total assets
R&D/Sales	R&D expenditure/total sales
ROA	Income before extraordinary items/total assets.
ROE	Income before extraordinary items/stockholders equity
Special/Assets	Special items/total assets.
Total volatility	Daily total volatility over the last year.
Trade secrecy	One if insiders' firm discloses "trade secrecy" or "trade secret" from 10-K filings on SEC's EDGAR database, and zero otherwise
Trade secrecy of tech. peers	Technology-weighted trade secrecy of technology-linked peer firms
Treatment Index	Average of the indicator variable, equals to 1 if the headquarters are located in one of FC states (California, Delaware, Illinois, Kansas, Minnesota, North Carolina, Utah, and Washington) and 0 otherwise, among technology-linked peer firms.
Transaction characteristics:	
Annual Purchase	One if insiders engage in purchase transactions following *techret* over year *t*.
BHR	Market-adjusted buy-and-hold returns over the 180 days following the transaction date. For sales transactions, we buy-and-hold returns are multiplied by -1.
Blackout period	One if the transaction occurs in the blackout period (i.e., the calendar day window (-46,1), where day 0 is the quarterly earnings announcement date), and zero otherwise
Carhart	Average daily alpha (intercept) from the four-factor Fama and French (1993) and Carhart (1997) model estimated over 180 days following the

	transaction date in percentage. For sales transactions, Carhart alpha is multiplied by -1.
Equity ownership by each trader	Equity ownership by each trader before transaction
Opportunistic (Routine) trading volume	Dollar value of opportunistic (routine) insiders' purchase transaction divided by market capitalization
Opportunistic Purchase $_t$	One if insiders engage in opportunistic purchase transactions after *techret* exists, and zero otherwise.
Past return	Market-adjusted buy-and-hold returns over 180 days prior to the transaction date
Purchase $_t$ (Purchase $_{t-1}$)	One if insiders engage in purchase transactions in month t (t-1) following *techret* in month t-1 (t-2)
Trading volume	Dollar value of purchase transaction divided by market capitalization
Transaction size	Natural logarithm of dollar amount of each trader's transaction
Insider characteristics:	
Industry expertise	One if an insider has expertise as top management of the public firm whose three-digit SIC code is the same as that of the focal firm, and zero otherwise
Ivy league	One if an insider holds an undergraduate degree from Ivy league schools, and zero otherwise