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Do insiders trade on innovation?

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ABSTRACT

We find that pure insider share purchases—which we define as insider purchases over two successive years without any corresponding sales—are a strong predictor of a firm's patent applications. The predictability increases with the quality of the patent: Applications for the highest-quality, breakthrough patents increase by 21% in the year following pure insider purchases in our sample. These purchases are associated with large abnormal stock returns of 1.1% per month (14% annualized) over the subsequent three-year period. We also document that stock price responds less to the subsequent announcement of the grant of patent if the application for the patent has been preceded by pure insider purchases, consistent with the idea that insider purchases reveal information about future firm innovation. Our evidence has implications for understanding insider trading within technology companies that have become a dominant feature of US stock markets in recent decades.

1. Introduction

Do insiders trade opportunistically and earn abnormal profits by exploiting private information about upcoming corporate events? This issue is enduring. Researchers have examined insider trading before corporate events such as earnings announcements, dividend initiations, mergers and acquisitions, stock repurchases and grants of stock options.[1] Yet, there has been little investigation of insider trading before firms' successful innovation outcomes. This is intriguing because the importance of innovation for firms has been emphasized in both the economics and finance literatures, and studies provide evidence of a positive relationship between innovation and the market value of firms (Hall et al., 2005; Atanassov, 2013; Kogan et al., 2017). This paper studies insider trading at technology firms before they apply for the grant of important patents.

A priori, the incentives for insiders to trade on their firms' innovation outcomes may be stronger than those for other corporate events for at least two reasons. First, the information advantage provided by innovation generally lasts longer than many other events such as quarterly earnings announcements, dividend initiations, and mergers and acquisitions. Innovation can take several years from idea generation to the grant of a patent. During this period, insiders are likely to know more about the success or failure probabilities of innovation projects than outsiders. The long duration of the information advantage is especially important because it provides the opportunity for insiders to side step Section 16(b) of the Securities and

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[1] For instance, Sivakumar and Waymire (1994) and Wang et al. (2012) study insider trading around earnings announcements; John and Lang (1991) before dividend initiations; Keown and Pinkerton (1981), Sanders and Zdanowicz (1992), and Agrawal and Jaffe (1995) before mergers and acquisitions; Vermaelen (1984), Lee et al. (1992), Louis and White (2007) before stock repurchases; and Yermack (1997) before the grant of CEO stock options.

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Exchange Act of 1934, which prohibits them from making money on purchase of shares that are then sold (or vice versa) within a 6-month window.[2] Second, unlike other corporate events, a firm's R&D effort tends to be unique, involving inputs that are intangible and idiosyncratic. Competitive pressures reinforce the need to keep information about innovation private. Outsiders therefore may not be able to anticipate innovation outcomes based on observing a company's competitors or the industry as a whole (Titman and Wessels, 1988). In contrast, for corporate events such as earnings or mergers and acquisitions, it may be possible for outsiders to anticipate, at least partially, a firm's outcome by carefully observing similar outcomes for its competitors and industry.

To investigate whether insiders increase their holdings of a firm's equity prior to important patent applications, we put together firm-year data that combines patent and insider trading datasets for US publicly held companies. Our primary analyses are based on panel data regressions where we regress patenting activity in a year on insider trading in the preceding years and controls. We measure patenting activity by the total number of patent applications in a year. Importantly though, we also classify patents by quality—based on the future citations the patents receive in the same technology class and year—and use measures of patenting activity of varying quality as alternate dependent variables to explore the possibility that the incidence of insider purchases depends on the quality of the future innovation. To construct our primary explanatory variable, we follow prior literature and define *pure* purchase years as those in which top executives purchase firm equity for two consecutive years without any corresponding sale. About 7 % of the firm-year observations in our sample qualify as pure purchase years. We include firm fixed effect in all our regressions. This ensures that time-invariant firm characteristics do not drive our results, and we relate within-firm variation over time in the patenting activity with lagged insider trading.

Our results indicate that purchases by top executives are followed by significantly better innovation outcomes for firms. Our estimates of Poisson regressions indicate that the number of patent applications increases by about 14 % (z-statistic = 3.43) in the year following pure purchases by insiders. Interestingly, the predictability of insider purchases for firm innovation increases monotonically as we move from low quality to high quality innovation. While the predictability is weak for the lowest quality patents, which we define as those with no future citations, it becomes stronger as we move to breakthrough patents, which we define alternately as those that fall in the top 10 % or top 5 % of their technology class and year. The number of top 5 % patents increase by about 21 % following insider purchases. The results are robust to the use of OLS estimation, inclusion of only opportunistic insider trades (Cohen et al., 2012), and alternate definitions of insiders. We also obtain similar results when we implement a difference-in-difference analysis, in which we compare change in future innovation for 'treated' firms that experience insider purchases relative to that for the control firms that are matched on industry and year but don't experience insider purchases.

Although the literature on insider trading find mixed evidence of the informativeness of insider sales, we also examine the relationship between insider sales and future firm innovation. We define pure insider sales years as those in which insiders sell over two consecutive years without any purchases. We find that insider sales have no predictive ability for the total number of patent applications a firm files in the following year. However, when we break down the patents by quality, we find an interesting pattern that is a mirror image of that for insider purchases. Insider sales are positively and significantly associated with low quality patents, but the association becomes weaker and turns negative, though statistically insignificant, as we move towards higher quality patents. The evidence that insider sales predict the future applications for poor-quality patents is consistent with the idea that insiders sell in anticipation of failed firm innovation. Insiders are likely to have superior knowledge of the ongoing progress about the R&D capabilities of the firm, including possible problems with innovation processes such as the turnover of key technicians or researchers and the failure to pass a particular phase. Our results for insider sales therefore reinforce the private information hypothesis in which insider trades are driven, at least partially, by knowledge about firm innovation.

To estimate the gains that come from insider purchases before firm innovation, we examine the profitability of pure insider purchases that precede the filing of the top 10 % of the patents. We employ a calendar-time portfolio approach, and estimate abnormal returns associated with individual insider purchases based on the intercepts of Fama-French (1993) three-factor regressions, with returns calculated for the subsequent 1-, 3-, 6- and 36-month (or 3-year) windows following the trade. We find that in the month following the purchase, which is the month in which the information about the trade became public in much of our sample period, the average abnormal stock return is 1.9 % (t-statistic = 1.87), consistent with prior literature that finds that insider trades move the prices when information about them becomes public (Seyhun, 2000). However, more interesting and novel is our evidence about the long-term returns associated with pure insider purchases before important innovations. Over the 3-year period, the average abnormal return is 1.1 per cent per month (14 % annualized, t-statistic = 2.82). This large long-term return is consistent with the idea that it takes a long time before private information about firm's breakthrough innovation becomes public. They also reinforce the unique nature of private information about innovation relative to that of other corporate events.

If insider purchases that precede innovation are indeed motivated by private information about impending firm innovation, one might expect that they would lead to stock prices partly incorporating such private information, leading to a smaller stock price reaction when the news is subsequently publicly announced. Large abnormal stock returns that we document for insider purchases in the previous section reinforce this possibility. To test this prediction, we rely on the recent influential

[2] While insider trading can also be prosecuted under the antifraud provisions of Rule 10b-5 of the Securities and Exchange Act of 1934, Section 16(b) provides a stronger check on insider trading because it requires little direct evidence that insider trading was motivated by private information. We review the US insider trading laws in more detail in the next section.

work of Kogan, Papanikolaou, Seru and Stoffman (2017, KPSS hereafter). They argue that much of the information about a successful patent becomes public at the time of the announcement of the grant of the patent by the United States Patent and Trademark Office (USPTO), and calculate the market value of each patent by quantifying the abnormal stock return in the days surrounding the announcement. We examine whether the market value estimates computed by KPSS are systematically lower for the patents that are preceded by pure insider purchases. We regress the market value estimate on our indicator variable *Pure Insider Purchase* and controls. The results indicate that the coefficient on *Pure Insider Purchases* is −45.7 (*t*-statistic = 1.75), implying that the incidence of pure insider purchases is associated with a reduction in the estimated value of the patent by about $46 million. Given that the mean market value of the patent is $344 million in our sample, this is an economically meaningful amount. The results are therefore consistent with the idea that insider purchases before innovation help assimilate private information about future firm innovation into stock prices before the information subsequently becomes public.

Our study is a natural extension of the work of Aboody and Lev (2000), who compare returns to insiders in R&D-intensive and non-R&D firms and find that gains to insiders are significantly higher in R&D firms. R&D expenditure, however, is an input rather than the output of a firm's innovation efforts and so can proxy for any number of other firm attributes. For instance, R&D could be positively correlated with general mispricing of the firm's stock.[3] Higher insider trading profits could simply be due to prices of R&D firms deviating more from their fundamental values rather than due to trading on impending innovation outcomes. That is, managers of these firms may be trading on publicly available information, and not necessarily on private information, to make additional profits.[4] By more directly tying insider trading with the success and failure of a firm's innovation outcomes, our evidence indicates that managers of publicly listed US technology firms can use opportunistic insider trading to capture a larger share of the gains form firm innovation than that allowed through formal contracts.

Our findings also contribute to the recent debate on the causal effect of insider trading *laws* on firm innovation. Levine et al. (2017) and Blank et al. (2019) find that stricter laws are associated with greater innovation, and attribute this to stricter laws facilitating greater equity financing. In contrast, Hussinger et al. (2018) find that stricter insider trading laws reduce innovation and attribute this to stricter laws reducing incentives for managers to engage in innovation. A maintained assumption in all these studies is that insiders do engage in trading to benefit from their knowledge of firm innovation. Our study validates this assumption. In addition, the pattern of gains from insider trading that we quantify can inform the debate on the desirability and nature of the insider laws for technology firms. While we leave it to readers to decide whether or not the insider trading behavior we document needs to be viewed as opportunistic rent-seeking behavior or a reasonable alternative compensation mechanism for managers of technology firms, it appears as if the six-month embargo window over which Section 16(b) bars insiders from trading on their information is too short to restrict insider trading on innovation. Regulators may need to widen this period if they want to clamp down insider trading on innovation among technology firms.

Finally, our work also speaks to the recent innovation literature that attempts to quantity the market value of patents by quantifying the stock price reaction around the announcement of the grant of patents (KPSS). The reliability of these market value estimates is based on the assumption that the announcement of the grant of patents is the precise point in time at which the information about firm's success with patenting becomes public. We provide evidence that suggests that this assumption does not fully hold for those patents that are preceded by insider purchases. For these patents, the estimates in KPSS are likely to understate the true market value.

The rest of the paper is organized as follows. Section 2 provides details of the institutional context in which insider trading and patenting activities take place in the US. Section 3 discusses data and methodology. Section 4 presents our main results. In Section 5, we examine the returns associated with insider purchases. Section 6 examines whether stock price reaction to the announcement of the grant of patent is affected by prior insider purchases. Section 7 explores the cross-sectional variation in the predictability of insider trading for firm innovation. Section 8 concludes.

2. Institutional setting for insider trading and patenting

2.1. Insider trading laws

Insider trading restrictions in the US are covered by the antifraud provisions of the Securities and Exchange Act of 1934, specifically Rule 10b-5 and Section 16b. Rule 10b-5 prohibits corporate officers and directors or other insider employees from using confidential corporate information to reap a profit (or avoid a loss) by trading in the company's stock. This rule also prohibits "tipping" of confidential corporate information to third parties. While this rule has been used in litigation against insider trading, it requires plaintiff to provide proof that a trade was motivated by inside information. In contrast, Section 16(b), sometimes known as short-swing rule, is easier to enforce and does not require such a proof. A short-

[3] Barth et al. (2001) find that greater research and development expenses are associated with greater analyst coverage. They interpret the evidence as consistent with such firms being more opaque and thus creating a greater demand for information.

[4] The idea that insiders can predict stock price movements because they are able to exploit the mispricing of the stock and not necessarily because they use any private information has also been proposed in prior work. See, for example, Lakonishok and Lee (2001), who find that insiders' ability to time the market can be explained partially by the mispricing of stocks.

swing trade is defined as a purchase and a subsequent sale (or a sale followed by a purchase) within a six-month period. Section 16b requires insiders to return all profits from such trades to the corporation.

Because it does not require proof that insider trade was motivated by private information, the implementation of Section 16(b) does not tie up *SEC* resources and any shareholder can initiate the legal action. In practice, due to free-rider problem, lawsuits based on Section 16(b) are initiated by lawyers who can easily become a shareholder by buying only one share and file a lawsuit. They can also claim their legal fees whenever insiders violate this rule. This rule is therefore attractive because it uses free market forces, rather than large amounts of public expenditures, for enforcement (Agrawal and Jaffe, 1995). However, it is also known that the rule has an important loophole, in that, an insider can sell the share six months and one day after buying it and avoid violating the rule.[5] Therefore, while Section 16(b) is deemed effective in curbing the use of inside information that comes out within the 6-month period, such as quarterly earnings announcements, it is not clear whether it can eliminate insider trading on information that comes out after the 6-month window (Agrawal and Jaffe, 1995; Seyhun, 2000).

Besides the Securities and Exchange Act of 1934, a number of court cases, such as the Cady, Roberts decision, the Texas Gulf Sulphur indictment, and the Texas Gulf Sulphur decision have strengthened insider trading regulations. Furthermore, the Insider Trading Sanctions Act of 1984 (ITSA), the Insider Trading and Securities Fraud Enforcement Act of 1988 (ITSFEA) have increased penalties for insider trading. Finally, the Sarbanes–Oxley Act of 2002 have required more timely disclosures of insider trades.

Prior work on examining the usefulness of the US insider trading laws in inhibiting opportunistic insider trading is limited. Jaffe (1974) finds that profits to insiders did not fall following important case decisions, namely the Cady, Roberts decision, the Texas Gulf Sulphur indictment, and the Texas Gulf Sulphur decision. Seyhun (1992) concludes that abnormal returns to insiders increased but insider trading prior to earnings and takeover announcements diminished after ITSA. Agrawal and Jaffe (1995) examine whether the short-swing rule of Section 16(b) deters managers from trading before mergers. Consistent with the deterrent effect, they find that managers' purchases drop significantly before the announcement of merger.

2.2. Innovation and patenting process

Innovation and patenting entail a long-drawn process. It begins with idea generation, in many cases by the people who are directly involved with R&D. They slowly build knowledge about the innovation, though this knowledge may be tacit and ambiguous at early stages. If the innovation process proceeds successfully, the potential of an innovation becomes clearer and top management becomes aware of it. The firm then begins to identify elements that may be patentable. Patenting is especially important for firms that want to protect their intellectual property vigorously and often. The patent application process however is long and bureaucratic. The firm must develop an application that cites all prior innovations on which the intellectual property was based. The application requires that the underlying technology be codified and that all possible uses of the technology be specified.

Once an application is filed with the United States Patent and Trademark Office (USPTO), it may take years before the patent is granted. On average, the time between the application and the grant of the patent is about two and half years (Hall et al., 2001).[6] During this patent pending period, the firm may begin to use the innovation in its product line, though they would generally try to keep the innovation secret from the rivals. As per the requirement of The American Inventors Protection Act of 1999, USPTO makes public the information about pending patent applications 18 months after the applications have been filed. Even after a patent is granted, its full potential may still not be fully visible to investors. This is partly because an innovation may not actually appear in a company's products immediately. In fact, many patents are never used in the company's products. For those that are, it can take a long time before the performance of the products based on the innovation are fully assessed in the marketplace. Finally, for breakthrough patents which provide building blocks for further innovation, it may take years before subsequent patents building upon the original technology are applied for and granted.

The innovation process can therefore be divided into three distinct stages. Stage 1 begins with the idea generation and ends with the filing of the patent application with USPTO. Stage 2 spans the period between the filing of the patent and its eventual grant by USPTO. Finally, stage 3 spans the period after the grant of the patent, in which the company tries to commercialize the new technology or use it as a building block for further innovation.

2.3. Timing of insider trading on innovation

Because managers may possess an information advantage relative to outside investors at every stage of the innovation process, they potentially may have opportunities to trade at different stages of the innovation process. However, if managers have strong foresight, the opportunities to profit may be greater during the first stage when managers are developing a patent application. This is the time period in which the full potential of an innovation should first be revealed to top man-

[5] *SEC* Rule 10b5-1 offers another way to bypass the constraint of Section 16(b). Established by the Securities and Exchange Commission (*SEC*) in 2000, this rule allows insiders to trade the company's stock as long as they preplan these transactions. Under the rule, insiders can establish a written plan with their brokers that details a predetermined time when they will buy or sell shares, to avoid the accusations of trading on material private information.

[6] https://www.uspto.gov/aia_implementation/aia_section_10_ria_doc-omb_9-6-12.pdf.

agers since efforts are under way to codify the knowledge in detail for patent application. There may be less new knowledge revealed to top managers in the later periods since much of the information about the innovation is already codified at the patent application stage. Furthermore, the details of the innovation may slowly become public over time after stage 1, which can reduce opportunities to profit in later periods. We therefore hypothesize that insiders primarily engage in opportunistic trading during stage 1.

It is possible, nevertheless, that because their information advantage lasts beyond stage 1, managers also trade on their private information during later stages. However, this would suggest lower level of foresight by managers about their firm's innovation. For example, it may be that top managers only become aware of the true importance of patents at the time that patent applications are filed (e.g., a lag as the information travels in the management hierarchy). This implies that top managers are out of the loop or otherwise uninvolved in R&D investment decisions and technology development until its fruits are quite apparent. The exact timing of insider trading therefore is an empirical question. While our primary hypothesis is that insiders trade during stage 1, we also investigate the possibility that they do so during stage 2.

While the conceptual discussion above is couched at the level of an individual patent, in our empirical analysis, we investigate the link between patenting and insider trading at the firm level. This is because the data on insider trading is available only at firm level and it is difficult to isolate it at the patent level. Fig. 1 illustrates the timeline of various variables used in our empirical analyses. We employ a firm-(calendar) year perspective, based on various stages of innovation process described above. Year $t + 1$ is the year in which the firm files a patent application with USPTO (and stage 1 ends). Insider trading on these patents is hypothesized to take place in the two preceding years—in years t and t-1. In our primary empirical analysis, we therefore examine the association between the patenting activity in year $t + 1$ and the insider trading in years t and t-1.

3. Sample construction and variables measurement

This section describes the sample, defines variables and provides summary statistics. A detailed description of variable definitions is provided in Appendix A.

3.1. Sample construction

We construct our sample from several sources. The information about our primary dependent variable, firm innovation, comes from the 2010 version of the National Bureau of Economic Research (NBER) Database. This database provides the information about the patents companies file, their future citations, and the truncation correction weights to correct the well-known truncation bias in patents (described in detail below). We obtain the information about the technological field of each patent, which we use to determine the quality of the patent, from the Patent Network Dataverse made available by Li et al. (2014) that has more comprehensive coverage of technological fields compared to other available datasets. Both the NBER and Patent Network Dataverse ends their coverage in 2010. The market value of each patent, which is estimated based on the stock market response to the announcement of the grant of the patent, comes from the KPSS data. The information about our key explanatory variable, insider trading, comes from the Thomson Financial (TFN) insider filings database. It contains all insider trades reported to *SEC* from January 1986 onwards.[7] Data for the control variables come from multiple sources. We obtain the information about accounting variables from the Compustat Database available through Wharton Research Data Services (WRDS). The information on the percentage of a company' stock held by institutions is obtained from Thomson's Institutional Holding database. Stock returns data come from the monthly file of the Center for Research on Security Prices (CRSP).

Our sample consists of firms at the intersection of data on insider trading, firm innovation, and controls. Our sample period begins in 1988 because the insider trading data begins from 1986 and we need two years of information to construct our primary explanatory variable *Pure Insider Purchases*, as explained below. We end in 2008 because this is the last year for which the datasets from NBER and Patent Network Dataverse allow construction of reliable measures of firm innovation, as explained below. As is common in the innovation literature (Hall et al., 2005; Chava et al. 2013), we drop a firm from our sample unless it has at least one patent over the entire sample period.[8] Following prior work, we also drop financial and utilities firms. Our final sample includes 20,205 firm-year observations over the period 1988 to 2008.

3.2. Measures of firm innovation

By combining the datasets from NBER, Patent Network Dataverse and KPSS, we assemble annual information on patent assignee names, the number of patents, the citations made or received by each patent, the application year, and the grant date, among other items. As is common in prior literature we use the patent application year instead of the grant year to indicate the timing of innovation (Comanor and Scherer, 1969).

[7] The number of insider trades reported by TFN is very low in early years and increases substantially from 1996. We find that our results remain qualitatively similar when we begin our sample period from 1996.

[8] This is especially needed in our context because we include firm fixed effects in our regressions.

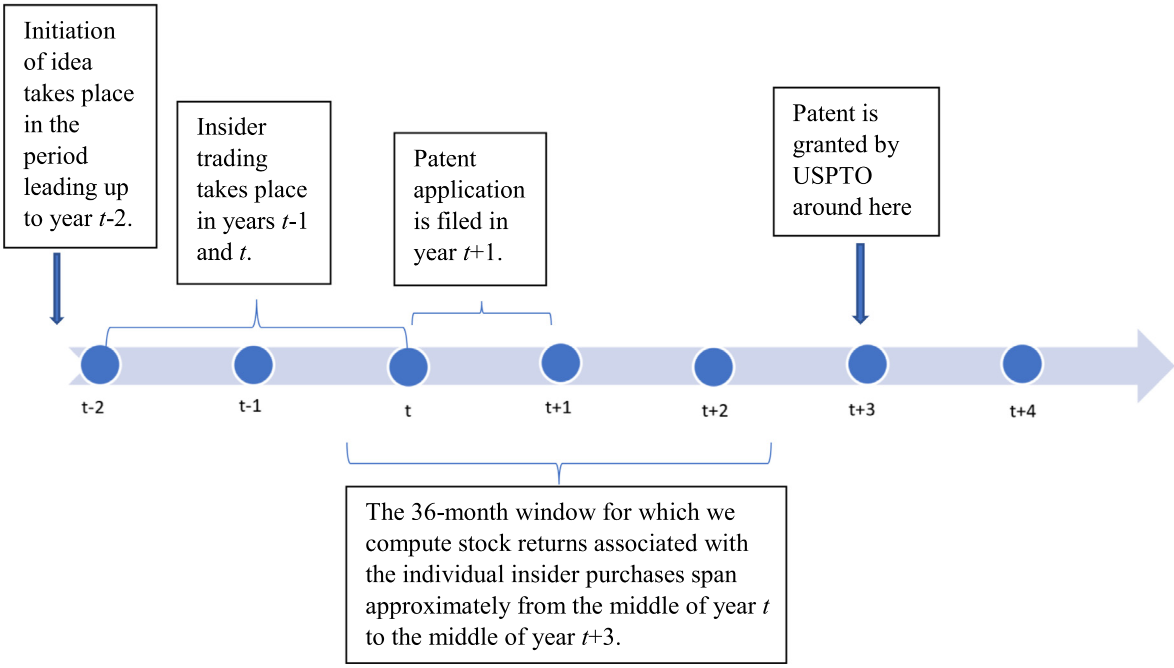

Fig. 1. Timeline of Various Stages of Innovation and the Insider Trading This figure describes the timeline of various stages of the patenting process. It also identifies the hypothesized timing of the insider trading that takes place based on innovation.

We make standard adjustments to the raw patents data common in the innovation literature. A well-known problem with raw patent data is the truncation problem. As noted earlier, patent applications have a long approval process that on average lasts for two and half years (Hall et al., 2001). Therefore, some patents applied for toward the end of the sample (2010) were not granted, and therefore are not included in the sample, which makes the number of patents applications lower in the last few years. These lags between application years and grant years change over time and over different technological fields. We follow the prior work and correct this truncation problem using truncation correction weights which are calculated from the application-grant lag distributions as described in Hall et al. (2001), and by leaving out the last two years in the sample (i.e., by restricting our sample to 2008). The number of citations received by the patents, on the other hand, carries an even bigger truncation problem. Patents granted keep receiving citations many years after our sample period, therefore the later it is in the sample period, the shorter the time period during which the patents can get citations, resulting in fewer citations of the patents with later application dates. This citation truncation problem is corrected by the fixed effect method described in Hall et al. (2001). Citations received for each patent are divided by the average number of citations received in the applied patent's technological field and in the application year to remove all fixed effects of year and technological field.

Our primary measure of a firm's innovation in a year is the number of patents it applies for in the year. We follow the prior innovation literature in choosing the application year of a patent instead of the grant year to indicate the timing of innovation (Comanor and Scherer, 1969). One drawback of using total number of patents as a measure of innovation is that it does not differentiate across innovation in terms of quality. Hall et al. (2005) show the impact of a patent on a firm's market value increases by its quality. We therefore also break down the patents a firm applies for in each year by quality classification and use each class of patents as alternate dependent variables in our regressions.[9] To determine the quality of a patent, we follow the prior literature (Balsmeier et al., 2017; Islam and Zein, 2020) and look at the number of future citations the patent receives in its technology class and year. We define high quality breakthrough patents alternately as those that either fall among the top 5 % or top 10 % of the distribution of future citations in the same technological class and year. These are labelled as *Top 5 % Patents* and *Top 10 % Patents*, respectively.[10] At the other extreme, the patents that receive no citations at all are classified as *Loser Patents*. The average quality patents, which fall in between the loser and top 10 % patents, are labelled as *Intermediate Patents*. We then sum the total number of patents a firm applies for in a year within each quality classification. This yields us measures of firm innovation in a year by quality.

[9] In addition, large technology firms routinely apply for a large number of patents every year and it may be more meaningful to tie only the high-quality patents for such firms to inside trading.

[10] For clarification, we note that the categories of top 10% and top 5% are not mutually exclusive. That is, the top 10% patents are a superset that include the patents labelled as top 5% as well.

3.3. Measures of insider trading

The Thomson Financial (TFN) insider filings database contains all insider trades reported to *SEC* from January 1986 onwards.[11] Following prior work (Alldredge and Cicero, 2015), we include only the observations that are deemed reliable and accurate by TFN (that is, transactions with the "cleanse code" "R, H, L, C, Y"). Furthermore, as in many prior studies (Seyhun, 1986; Lakonishok and Lee, 2001; Cheng et al., 2007), we focus on the trades of top five executives—CEO, CFO, COO, President, Chairman of the Board—and any Officer/Director holding more than 10 % of a class of shares.[12] These are the insiders who are more likely to have superior information compared to other insiders (Baesel and Stein, 1979). We also restrict the analysis to the open market transactions and private sale of securities (TFN transaction codes of "P" and "S"), since they are more likely to be driven by private information compared with the transactions related to stock options awards (Marin et al., 2008; Lakonishok and Lee, 2001; Seyhun, 1986). Finally, in our analysis of purchases, we drop firms that had no year in the entire sample period in which the number of insider purchases exceeded the number of insider sales, what we term a purchase year. We apply a similar filter in our analysis of sales.

To construct our insider trading variable, we follow previous literature (for example, Lee, 1997; Lin and Howe, 1990) and focus on "pure" insider trading activities, as such activities are more likely to be motivated by private information and constitute a clearer signal than a mixed insider trading pattern. Specifically, we define our main explanatory variable, *Pure Insider Purchases,* as a dummy variable that equals one if insiders engage in purchasing in both the current and the preceding years without any sale. We choose a period of two years because the findings of Lakonishok and Lee (2001) indicate that over longer horizons the predictive power of insider trades increase since laws restrict insiders from trading and profiting six months prior to important events. This may be especially relevant for insider trading on private information about innovation that becomes public over long period of time. If insiders purchase shares based on their private information about firms impending innovation success, we should observe that *Pure Insider Purchases* is positively associated with future firm innovation.

3.4. Control variables

Following the extant literature, we control for a host of firm characteristics that could confound the relationship between insider trading and a firm's future innovation output. These variables are computed for each fiscal year. We include Tobin's Q as it can proxy for growth opportunities of a firm and the potential for future innovation. Firms in our sample also differ widely in terms of their size as measured by *Total Assets*, which is naturally positively associated to the quantum of a firm's innovation output. We include the natural logarithm of total assets as a control to reduce the skewness in total assets. Return on Assets (*EBITDA/Total Assets*) is included as a firm's profitability, as a proxy for the commercial success of a firm's past portfolio of inventions and its financial constraints, both of which can influence future innovation. We include R&D intensity (*R&D/Total Assets)* as a control in all our regressions because both the dependent variable—innovation output—and the key explanatory variable—prior insider trading—are likely to be affected by it (Aboody and Lev, 2000). Institutional ownership (*IO*) can be a proxy for governance and can influence both future firm innovation (Aghion et al., 2013) and insider trading. Stock illiquidity has also been shown to influence firm innovation (Fang et al., 2014). We therefore include as a control Amihud's measure of illiquidity, (*Illiquidity*), which we calculated based on daily data for the year. Finally, we include past one-year stock returns (*Stock Returns*) to account for the recent changes in a firm's growth opportunities.

3.5. Summary statistics

Table 1 provides the summary statistics of the key variables used in our study. These are based on the distribution of pooled firm-year observations. All variables are winsorized at the 1st and 99th percentiles of their respective distribution. Our key explanatory variable, *Pure Insider Purchases*, has a mean of 0.07, indicating that about 7 % of the firm-year observations in our sample involve pure insider purchases. The distributions of the measures of firm innovation are heavily skewed, as is commonly documented in previous literature. The mean number of patents is 14 while the median is 1. Breakthrough innovation, by its very definition, is rarer. The mean (median) number of top 5 % patents is 0.91 (0). Because of the requirements of at least one patent during the sample period, the firms included are larger, have high Tobin's Q and are more R&D intensive than the typical listed firm in the CRSP dataset. The mean of the book value of the total assets and Tobin's Q are $1.4 billion and 2.49 respectively. The ratio of R&D to total assets is on average 11 %.

Data limitations necessitate limiting our analyses to the period ending in the year 2008, as noted earlier. To the extent that the nature and mix of corporate innovation have changed since then *and* these changes have led to changes in the incentives for insider trading, some of our results may not hold for the more recent period. To explore this possibility, in untabulated results we examine the industry distribution of the patenting firms in our sample. Specifically, we look at the representation of the high technology industries in our sample. To identify these, we follow the classification used in

[11] The number of insider trades reported by TFN is very low in early years and increases substantially from 1996. We find that our results remain qualitatively similar when we begin our sample period from 1996.

[12] As reported in a later section, we find qualitatively similar results when we restrict our analyses to only the top 5 executives and drop officers or directors holding more than 10% of a class of share.

Table 1
Summary Statistics.

Variables	Mean	Standard Deviation.	Min.	25th Percentile	Median	75th Percentile	Max.
Pure Insider Purchases	0.07	0.26	0.00	0.00	0.00	0.00	1.00
Total Patents	14.24	56.82	0.00	0.00	1.00	5.00	530.13
Loser Patents	2.97	16.40	0.00	0.00	0.00	1.00	265.00
Intermediate Patents	9.54	43.06	0.00	0.00	1.00	3.00	452.00
Top 10 % Patents	1.85	8.32	0.00	0.00	0.00	1.00	102.00
Top 5 % Patents	0.91	4.42	0.00	0.00	0.00	0.00	63.00
Patent Value (nominal, in million $)	344	1,758	0.00	0.00	1.6	27	16,337
Tobin's Q	2.49	2.23	0.62	1.22	1.71	2.81	13.59
Total Assets (in million $)	1,376	5,673	1.7	35	118	547	78,315
ROA	−0.07	0.28	−1.32	−0.10	0.03	0.08	0.25
R&D/Total Assets	0.11	0.15	0.00	0.02	0.06	0.13	0.93
IO	0.39	0.28	0.00	0.15	0.36	0.61	1.04
Illiquidity	2.15	8.00	0.00	0.01	0.08	0.71	117.60
Stock Returns	0.18	0.70	−0.85	−0.26	0.04	0.40	2.76

This table shows the descriptive statistics for the key variables. The sample consists of 20,205 firm-year observations for 1,741 unique firms over the period 1988–2008. *Pure Insider Purchases* is a dummy variable that takes the value of one if there is at least one insider purchase in the current as well as the preceding year without any insider sales, and zero otherwise. *Total Patents* is the number of total patents applied for by the firm during the year. *Loser Patents* is the number of patents applied for that received no citation in the future. *Intermediate Patents* is the number of patents applied for that are neither loser patents nor top 10% patents as defined below. *Top 10% Patents* is the number of patents applied for that fall among the top 10% of their technological class and year in terms of future citations received. Likewise, *Top 5% Patents* is the number of patents applied for that fall among the top 5% of their technological class and year in terms of future citations received. *Patent Value* is the market value of all the patents applied for by the firm in the year. Market value data are obtained from KPSS. *Tobin's Q* is the ratio of book value of assets minus book value of equity plus market value of equity to the book value of total assets. *ROA* is return on assets, computed by dividing earnings before interest, taxes, depreciation and amortization by total assets. *R&D/Total Assets* is R&D expenditure divided by total assets. *IO* is the institutional ownership measured at the end of the year. *Illiquidity* is Amihud's measure of illiquidity for the year. *Stock Returns* is the annual stock return. Further details about the calculation of these variables are provided in Appendix I. All variables are winsorized at the 1st and 99th percentiles of their respective distribution.

Loughran and Ritter (2004).[13] In the full sample, out of 1,741 unique firms, the percentage that belong to technology industries is around 37 %. When we divide our sample into two sub-periods from 1988 to 1997 and 1998–2008, the percentage of high technology firms increases only slightly from 34 % to 38 % from the first to the second sub-period. When we look at the number of patents, we also find that even though the total number of patents increases substantially in the later period, the percentage of patents filed by high technology firms increases only moderately. In other words, the share of the high-technology firms in the patenting activities does not change dramatically across the two sub-periods. We arrive at similar conclusion when we use Fama-French 12-industry classification and identify Business Equipment (Computers & Software) and Healthcare, Medical Equipment, and Drugs as high technology industries.

4. Main results: Insider trading and innovation

In this section, we examine whether and how the incidence of inside trading is related to future firm innovation.

4.1. Baseline results

To understand whether the insider trading predicts firm innovation, we regress measures of firm innovation on lagged values of the indicator for pure insider purchases and controls. Because the dependent variables are count variables, we estimate the models as Poisson regressions (Hausman et al., 1984; Sunder et al., 2017), as specified below.

$$ln(Innovation_{i,t+1}) = \beta_0 + \beta_1 PureInsiderPurchase_{i,t} + \gamma Z_{i,t} + Firmfixedeffects + Yearfixedeffects + \in_{i,t+1} \quad (1)$$

The subscripts i and t depict firm and year, respectively. The dependent variable is either the number of total patents or the number of patents of certain quality. Our main explanatory variable, *Pure Insider Purchase*, is a dummy variable that takes the value of one if the firm experienced insider purchases in both year t and t-1 without any simultaneous insider sale. Z is a vector of firm-level control variables introduced previously. Year fixed effects control for changes in insider trading over time that relate to changes in general macroeconomic and regulatory environment. Importantly, we also include firm fixed effects in regressions to control for any unobserved heterogeneity across firms that is time-invariant. Therefore, the identification in our model comes from within-firm variation over time in insider trading that relates to future innovation of the firm. To account for error dependencies across firm and year, the standard errors are adjusted for two-dimensional clustering at the firm and year level.

[13] Specifically, high technology industries are those with the following SIC codes: 3571, 3572, 3575, 3577, 3578 (computer hardware), 3661, 3663, 3669 (communications equipment), 3671, 3672, 3674, 3675, 3677, 3678, 3679 (electronics), 3812 (navigation equipment), 3823, 3825, 3826, 3827, 3829 (measuring and controlling devices), 3841, 3845 (medical instruments), 4812, 4813 (telephone equipment), 4899 (communications services), and 7371, 7372, 7373, 7374, 7375, 7378, and 7379 (software).

Table 2
Insider Purchases and Future Firm Innovation: Poisson Regressions.

Explanatory Variables	Dependent Variable =				
	Total Patents	Loser Patents	Intermediate Patents	Breakthrough Patents	
				Top 10 % Patents	Top 5 % Patents
	(1)	(2)	(3)	(4)	(5)
Pure Insider Purchases	0.139***	0.075*	0.146**	0.163**	0.206***
	(3.43)	(1.68)	(2.24)	(2.38)	(2.87)
Tobin's Q	0.019	0.066**	0.013	−0.011	−0.013
	(1.44)	(2.45)	(0.91)	(-0.62)	(-0.55)
Log (Total Assets)	0.423***	0.424***	0.454***	0.364***	0.333***
	(6.96)	(4.10)	(6.46)	(4.62)	(3.18)
ROA	0.324*	0.559*	0.231	0.214*	0.103
	(1.88)	(1.73)	(1.63)	(1.80)	(0.68)
R&D/Total Assets	1.840***	1.874***	1.909***	1.625***	1.585***
	(5.35)	(3.52)	(5.69)	(3.79)	(3.29)
IO	−0.096	−0.551	−0.191	0.016	0.005
	(-0.65)	(-1.51)	(-1.13)	(0.07)	(0.02)
Illiquidity	−0.074***	−0.108***	−0.083***	−0.060	−0.076
	(-3.15)	(-2.93)	(-3.29)	(-1.64)	(-1.51)
Stock Returns	0.048**	0.042	0.056**	0.074***	0.088***
	(2.22)	(1.19)	(2.15)	(2.81)	(2.64)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.900	0.851	0.898	0.781	0.716
# of Firm-Year Obs.	20,205	14,632	19,248	13,536	10,528
# of Unique Firms	1,741	1,156	1,609	1,080	813

This table presents estimates from panel fixed effects Poisson regressions. $ln(Innovation_{i,t+1}) = \beta_0 + \beta_1 PureInsiderPurchase_{i,t} + \gamma Z_{i,t} + Firmfixedeffects + Yearfixedeffects + \epsilon_{i,t+1}$.
The dependent variable is innovation productivity for firm *i* in year *t* + 1, measured in term of the number of patents of varying quality applied for during the year. *Total Patents* is the total number of patents. *Loser Patents* is the number of patents that received no future citations. *Intermediate Patents* is the number of patents that are neither loser patents nor top 10 % patents as defined below. *Top 10 % Patents* is the number of patents that fall among the top 10 % of their technological class and year in terms of future citations. Likewise, *Top 5 % Patents* is the number of patents that fall among the top 5 % of their technological class and year in terms of future citations. The key explanatory variable is *Pure Insider Purchases*, a dummy variable that takes the value of one if there is at least one insider purchase year *t* and *t*-1 without an insider sale, and zero otherwise. The vector of *Z* firm-level controls includes the following. *Tobin's Q* is the ratio of book value of assets minus book value of equity plus market value of equity to the book value of total assets. *ROA* is the return on assets. *R&D/Total Assets* is R&D expenditure divided by total assets. *IO* is the institutional ownership measured at the end of the year. *Illiquidity* is Amihud's measure of illiquidity for the year. *Stock Returns* is the annual stock return. The sample period is 1988–2008. The *z*-statistics reported in parentheses are based on robust standard errors that are clustered at the level of both firm and year. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 2 presents our baseline results. In Column (1), we report the regression estimates when the dependent variable is total number of patents. The coefficient estimate on *Pure Insider Purchases* is 0.14 (*z*-statistic = 3.43), implying that the incidence of pure insider purchases is associated with an increase in firm innovation by 14 % in the following year. The economic magnitude of this predictability therefore appears large. In Columns (2) through (5), we use number of patents sorted on quality as alternative dependent variables. Because we include firm fixed effects, these regressions are estimated from fewer observations as observations for whom the dependent variable doesn't vary over time get dropped. The results reveal an interesting pattern: The coefficient estimates on *Pure Insider Purchases* increase monotonically as we move from low to high quality patents. For *Loser Patents*, the coefficient estimate is 0.075 (*z*-statistics = 1.68). It increases and becomes large at 0.206 (*z*-statistic = 2.87) for *Top 5 % Patents*, implying that filing of breakthrough patents increases by 21 % following pure insider purchases. This pattern of results is exactly what one expects to observe if insiders trade on their private information about firm innovation, which likely includes not just the knowledge about the quantity of the firm's innovation but also its quality. Because higher quality patents lead to a greater increase in a firm's market value (Hall et al., 2005), insiders are more likely to purchase stock before the filing of higher quality patents. Overall, therefore, the results in Table 2 indicate that pure insider purchases are important predictors of firm innovation, especially breakthrough innovations.

The coefficients on the control variable in Table 2 generally show up with expected signs. The size of the firm, measured by the book value of total assets, is positively correlated with firm innovation across all columns, indicating that larger firms file for more patents. Likewise, R&D intensity, which represents the key innovation input, also has large positive coefficient estimates across all columns. Finally, past one-year stock returns that account for the recent changes in firm's growth opportunities are positively associated with firm innovation. All these relationships are consistent with the findings of previous innovation literature (Aghion et al., 2013; Sunder et al., 2017).

Table 3 reports the OLS estimates of our model for the purpose of comparability with prior work that employs OLS regressions to analyze firm innovation (e.g., Hirshleifer et al., 2012). The dependent variable now is the natural logarithm of one plus the number of patents. The addition of one before taking the log transformation helps retain firm-year observations with zero patents or citations. The coefficient estimates for *Pure Insider Purchases* in the table are somewhat weaker but

Table 3
Insider purchases and future firm innovation: OLS regressions.

Explanatory Variables	Dependent Variable = ln *(1 + Innovation)*				
	Total Patents	Loser Patents	Intermediate Patents	Breakthrough Patents	
				Top 10 % Patents	Top 5 % Patents
	(1)	(2)	(3)	(4)	(5)
Pure Insider Purchases	0.044**	−0.037	0.049	0.027	0.049**
	(2.08)	(-1.51)	(1.62)	(1.14)	(2.11)
Tobin's Q	0.013***	0.019***	0.011**	0.008*	0.010**
	(2.90)	(3.33)	(2.29)	(1.85)	(2.58)
Log (Total Assets)	0.249***	0.143***	0.232***	0.134***	0.107***
	(9.81)	(5.68)	(8.91)	(5.92)	(4.89)
ROA	0.048	−0.010	0.056	0.009	−0.001
	(1.12)	(-0.20)	(1.23)	(0.25)	(-0.04)
R&D/Total Assets	0.688***	0.174*	0.689***	0.332***	0.290***
	(6.52)	(1.73)	(6.48)	(3.79)	(3.44)
IO	−0.049	−0.110	−0.085	−0.043	−0.085
	(-0.74)	(-1.52)	(-1.28)	(-0.81)	(-1.59)
Illiquidity	−0.022***	−0.010	−0.021***	−0.013*	−0.017**
	(-3.47)	(-1.26)	(-3.32)	(-1.85)	(-2.29)
Stock Returns	0.020**	0.001	0.018*	0.012	0.007
	(2.77)	(0.07)	(2.07)	(1.63)	(0.83)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.818	0.734	0.778	0.749	0.712
# of Firm-Year Obs.	20,205	14,632	19,248	13,536	10,528
# of Unique Firms	1741	1156	1609	1080	813

This table presents estimates from the following panel fixed effects ordinary least squares (OLS) regressions.$ln(1 + Innovation_{i,t+1}) = \beta_0 + \beta_1 PureInsiderPurchase_{i,t} + \gamma Z_{i,t} + Firmfixedeffects + Yearfixedeffects + \epsilon_{i,t+1}$.
The dependent variable is innovation productivity for firm *i* in year *t* + 1, measured as the natural log of one plus the number of patents of varying quality applied during the year. *Total Patents* is the total number of patents. *Loser Patents* is the number of patents that receive no future citations. *Intermediate Patents* is the number of patents that are neither loser patents nor top 10 % patents as defined below. *Top 10 % Patents* is the number of patents that fall among the top 10 % of their technological class and year in terms of future citations. Likewise, *Top 5 % Patents* is the number of patents that fall among the top 5 % of their technological class and year in terms of future citations. The key explanatory variable is *Pure Insider Purchases*, a dummy variable that takes the value of one if there is at least one insider purchase in year *t* and *t*-1 without an insider sale, and zero otherwise. The vector of *Z* firm-level controls includes the following. *Tobin's Q* is the ratio of book value of assets minus book value of equity plus market value of equity to the book value of total assets. *ROA* is the return on assets. *R&D/Total Assets* is R&D expenditure divided by total assets. *IO* is the institutional ownership measured at the end of the year. *Illiquidity* is Amihud's measure of illiquidity for the year. *Stock Returns* is the annual stock return. The sample period is 1988–2008. The *t*-statistics reported in parentheses are based on robust standard errors that are clustered at the level of both firm and year. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

remain largely in line with what we report in Table 2. The coefficient estimates are positive and statistically significant at the usual levels when the dependent variable is *Total Patents* and *Top 5 % Patents*, but become statistically insignificant for lower quality patents. For *Loser Patents*, the coefficient turns negative, consistent with the idea that insiders reduce their share purchases when the firm's impending patents are of poor quality.

We next investigate the timing of the insider purchases before firm innovation. As discussed earlier, innovation is a long, drawn out process that spans several years. It typically takes a firm years before it can file an application with the USPTO for patenting an innovation. Once that is accomplished, it takes another two and half years, on average, before a patent application is granted by the USPTO, at which time the details of the application publicly accessible. Since a rule change in 2000, the USPTO now releases information about patent applications 18 months after its filing (KPSS). As a consequence, it is possible for insiders to retain their information advantage until the information about the patent application is made public by USPTO.

To investigate the timing of insider purchases associated with firm innovation, we include contemporaneous (in year *t*) and leading values (in year *t* + 1) of the variable *Pure Insider Purchases* in our regressions. If much of the insider purchasing takes place in the year of the filing of the patent or in the following year, when the information about the application has not yet been made public by USPTO, one would expect the coefficients on the additional variables to show up as positive significant. The results reported in Table 4 indicate that the additional variables are insignificant in the presence of lagged values for *Pure Insider Purchases*.[14] It therefore appears that insider purchases, which are motivated by private information about the firm's ongoing patenting activity, are mostly concentrated in the two years preceding the filing of the patent application. This timing seems intuitive in that these years represent the window in which the information advantage of insiders is likely to be the highest. In the period before this window, there may be too little information about the value of the patent as the innovation

[14] We also experiment with running regressions with only contemporaneous values of *Pure Insider Purchases* at time *t* or only the leading values at time *t*+1, and find their coefficients to be insignificant.

Table 4
Exploring the Timing of the Insider Purchases Around Filing of the Patents.

Explanatory Variables	Dependent Variable = Total Patents
Pure Insider Purchases (*t*)	0.140***
	(3.58)
Pure Insider Purchases (*t* + 1)	−0.008
	(-0.17)
Pure Insider Purchases (*t* + 2)	0.007
	(0.16)
Tobin's Q	0.019
	(1.45)
Log (Total Assets)	0.424***
	(6.95)
ROA	0.324*
	(1.89)
R&D/Total Assets	1.840***
	(5.35)
IO	−0.096
	(-0.65)
Illiquidity	−0.074***
	(-3.16)
Stock Returns	0.049**
	(2.18)
Firm Fixed Effects	Yes
Year Fixed Effects	Yes
Pseudo R-squared	0.900
# of Firm-Year Obs.	20,205
# of Unique Firms	1,741

This table explores the possibility of continued insider trading after the filing of patent applications. To explore this possibility, we include the lead values of the key explanatory variable *Pure Insider Purchases* for year *t* + 1 and *t* + 2 in the base model of Table 2, as follows..$ln(Innovation_{i,t+1}) = \beta_0 + \beta_1 PureInsiderPurchase_{i,t} + \beta_2 PureInsiderPurchase_{i,t+1} + \beta_3 PureInsiderPurchase_{i,t+2} + \gamma Z_{i,t} + Firmfixedeffects + Yearfixedeffects + \in_{i,t+1}$
As before, the model we estimate is a fixed effects Poisson regression. The dependent variable is *Total Patents*, which is the total number of patents filed in year *t + 1*. *Pure Insider Purchases* for year *t* is a dummy variable that takes the value of one if there is at least one opportunistic insider purchase in years *t* and *t*-1, without any opportunistic insider sales, and zero otherwise. *Tobin's Q* is the ratio of book value of assets minus book value of equity plus market value of equity to the book value of total assets. *ROA* is the return on assets. *R&D/Total Assets* is R&D expenditure divided by total assets. *IO* is the institutional ownership measured at the end of the year. *Illiquidity* is Amihud's measure of illiquidity for the year. *Stock Returns* is the annual stock return. The regressions are estimated using firm-year observations over the period 1988–2008. The *z*-statistics reported in parentheses are based on robust standard errors that are clustered at the level of both firm and year. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

is still a work-in-progress. Likewise, in the period after the patent application, the information about the patent would start filtering through to the market through the firm's own announcements and conference calls, and via media and analyst reports.

In untabulated analyses, we perform three other robustness checks on the main results reported in Table 2. First, we repeat our analysis after excluding the routine purchases by insiders. Cohen et al. (2012) define an insider purchase as routine if the same insider purchases the stock in the same month for three consecutive years. They show that routine transactions are not informative about future stock performance. Second, we exclude the purchases by large shareholders and focus on the trades initiated by the top five executives only, which include the CEO, CFO, COO, President, and Chairman of Board. Seyhun (2000, Ch. 3) argues that these executives are at the top of the "information hierarchy" of future firm performance, and their trades may contain more information about a firm's future performance. Finally, we include the lagged shareholdings of the insiders obtained from Form-5 filings as an additional control in our analysis. For each of these checks, our results remain qualitatively similar to those reported in Table 2.

4.2. Matched sample analysis

As noted earlier, we include firm and year fixed effects, so the identification in our base case regression in Equation (1) comes from changes in innovation within a firm over time, which we associate with changes in pure inside purchases. This framework accounts for unobservable heterogeneity across firms that is time invariant. Nevertheless, in this section, we adopt an alternative matched sample research design as a robustness check and to further mitigate concerns about endogeneity.

We begin by identifying a sample of 'treated' firm-year observations. These are those for which Pure Insider Purchase equals 1 in year *t*, that is, which experience insider purchases in years *t* and *t*-1, without any simultaneous inside sale. We then obtain matched sample of 'untreated' observations. Matching is done based on industry (i.e., Fama-French 49 Industry classification) and year, with replacement. All the matched observations come from those firms that never experience a pure insider purchase throughout our sample period. We examine the innovation for the treated and matched observations in year *t* + 1 relative to that of year/t^{-2}(−|-). We skip year *t* and *t*-1 for cleaner inference.

We then estimate a modified version of the regression in Table 2, as follows.

$$ln(Innovation_{i,t+1}) = \beta_0 + \beta_1 TreatedxAfter + Firmfixedeffects + Yearfixedeffects + \gamma Z_{i,t} + \in_{i,t+1} \quad (2)$$

Treated takes the value of one for observations that experience pure insider purchase, and zero otherwise. *After* takes the value one for the period after the insider purchase, and zero otherwise. The key explanatory variable is the interaction term, *Treated* × *After*, that represents the difference-in-difference (DID) estimator. It indicates how the innovation of treated firms changes after insider purchases relative to that for the matched firms that do not experience insider purchase. We do not include the stand-alone terms *Treated* and *After* because we include the firm and year fixed effects, which account for all unobservable differences in innovation across firms and years. As before, the dependent variable is innovation productivity, measured in term of the number of patents of varying quality applied for by the firm during the year. To draw cleaner inference, we estimate this model using only those treated firms that remain untreated in the surrounding years (i.e., in the years/ t^{-2}(−|-), *t*-1 and *t* + 1).

The results are reported in Table 5. In Column (1) where the dependent variable is *Total Patents*, the coefficient is positive though statistically not significant. As we move to the breakthrough patents—those that rank among the top 10 % and top 5 %—as the dependent variables, the coefficients become highly significant. The coefficient estimate on *Pure Insider Purchases* for *Top 5 % Patents* is 0.39 (*z*-statistic = 2.78), implying that the incidence of pure insider purchases is associated with an increase in firm innovation by 39 % in the following year over and above that of the matched firms. The results based on matched sample analysis in Table 5, therefore, also indicate that insider purchases are associated with large increase in the probability of breakthrough innovation in the future.

Table 5
Robustness Check: Matched Sample Analysis.

Explanatory Variables	Dependent Variable =				
	Total Patents	Loser Patents	Intermediate Patents	Breakthrough Patents	
				Top 10 % Patents	Top 5 % Patents
	(1)	(2)	(3)	(4)	(5)
After × Treated	0.024	−0.256	−0.035	0.267*	0.391***
	(0.39)	(-1.64)	(-0.39)	(1.85)	(2.78)
Tobin's Q	−0.029	0.009	−0.046*	−0.019	−0.177*
	(-0.91)	(0.21)	(-1.84)	(-0.21)	(-1.92)
Log (Total Assets)	−0.182*	−0.361**	−0.239**	0.209	−0.111
	(-1.66)	(-2.40)	(-2.34)	(0.63)	(-0.26)
ROA	0.476**	0.559***	0.906**	−0.124	0.385
	(2.18)	(2.90)	(2.48)	(-0.17)	(0.74)
R&D/Total Assets	1.444	0.481	2.554**	−0.176	1.832
	(1.25)	(0.36)	(2.13)	(-0.09)	(0.63)
IO	1.031***	1.180***	0.322	0.484	0.270
	(3.52)	(3.68)	(0.57)	(0.73)	(0.75)
Illiquidity	−0.105*	−0.058	−0.082**	0.012	−0.099
	(-1.85)	(-0.75)	(-2.21)	(0.09)	(-0.58)
Stock Returns	−0.071*	−0.154*	−0.103**	−0.001	0.096
	(-1.79)	(-1.66)	(-2.24)	(-0.01)	(0.64)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.952	0.903	0.951	0.862	0.799
# of Firm-Year Obs.	851	565	791	576	384

This table replicates the results in Table 2 using matched sample estimation. We identify pairs of treated and matched observations where the treated firms are those that experience pure insider purchase for two successive years/t and *t*, and matched observations are those without the insider purchase but from the same industry and year. For both the treated and matched firms, we collect innovation data for the period after (i.e., for the year *t* + 1) and before (i.e., year/t^{-2}(−|-)). We then estimate a modified version of the regression in Table 2, as follows $ln(Innovation_{i,t+1}) = \beta_0 + \beta_1 TreatedxAfter + Firmfixedeffects + Yearfixedeffects + \gamma Z_{i,t} + \in_{i,t+1}$.

After takes the value one for the period after the insider purchase, and zero otherwise. *Treated* takes the value of one for observations that experience pure insider purchase, and zero otherwise. The key explanatory variable is the interaction term, *After* × *Treated*, that represents the difference-in-difference (DID) estimator. It indicates how the innovation of treated firms changes after insider purchases relative to that for the matched firms that do not experience insider purchase. Because firm and year fixed effects are included, we do not include the stand-alone terms *Treated* and *After*. As before, the dependent variable is innovation productivity in the year, measured in term of the number of patents of varying quality applied for by the firm during the year. *Total Patents* is the total number of patents. *Loser Patents* is the number of patents that receive no future citations. *Intermediate Patents* is the number of patents that are neither loser patents nor top 10 % patents as defined below. *Top 10 % Patents* is the number of patents that fall among the top 10 % of their technological class and year in terms of future citations. Likewise, *Top 5 % Patents* is the number of patents that fall among the top 5 % of their technological class and year in terms of future citations. *Tobin's Q* is the ratio of book value of assets minus book value of equity plus market value of equity to the book value of total assets. *ROA* is the return on assets. *R&D/Total Assets* is R&D expenditure divided by total assets. *IO* is the institutional ownership measured at the end of the year. *Illiquidity* is Amihud's measure of illiquidity for the year. *Stock Returns* is the annual stock return. The *z*-statistics reported in parentheses are based on robust standard errors that are clustered at the level of both firm and year. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

4.3. Evidence from insider sales

The insider trading literature generally focuses less on insider sales than insider purchases. This is because insider sales and purchases are not perfectly symmetrical. Compared to insider purchases, insider sales are more likely to be hedging motivated (Peress, 2010; Wang et al., 2012) and also face greater litigation risk if they are suspected to be motivated by private information (Alldredge and Cicero, 2015). Furthermore, due to short sale constraints, insiders also need to own shares in order to engage in insider sales. Accordingly, many studies conclude that insider sales are not informative about future stock price performance (Lakonishok and Lee, 2001; Ravina and Sapienza, 2009). Nevertheless, a handful of studies document some systematic patterns associated with insider sales. Cheng et al. (2007) show that when insiders delay the disclosure of sales through Form-5 filing, the subsequent stock price decreases significantly. Likewise, Jagolinzer (2009) finds that even within the *SEC*'s Rule 10b5-1 insiders' preplanned sales transactions precede falling share prices and come after price increases. Rozeff and Zaman (1998) also argue that insiders' holdings decrease significantly following jumps in a stock's price. Cohen et al. (2012) document that opportunistic insider sales are associated with large abnormal negative returns in the future. In general, therefore, the evidence seems mixed in terms of the ability of insider sales to predict future firm performance.

Nevertheless, insider sales provide a useful setting in which to re-examine the association between insider trading and future firm innovation. If insider sales are motivated by private information, we might find that insiders sales increase (decrease) before the filing of low-quality (high-quality) patents. On the other hand, if they contain no predictability about future firm performance, they offer us a natural opportunity to conduct placebo tests to check the robustness of our main results. If the earlier findings in Table 2 are driven by some unobservable factors increasing insider trading before firm innovation, and not by insiders' desire to profit from their private information, we should expect similar results to hold for insider sales. We therefore examine the association between insider sales and future firm innovation in this section.

Table 6 reports the results. The dependent variable continues to be innovation, but the key explanatory variable now is *Pure Insider Sales*. This is defined analogously to *Pure Insider Purchases*. It equals one if insiders (CEO, CFO, COO, President,

Table 6
Insider Sales and Future Firm Innovation.

Explanatory Variables	Dependent variable =				
	Total Patents	Loser Patents	Intermediate Patents	Breakthrough Patents	
				Top 10 % Patents	Top 5 % Patents
	(1)	(2)	(3)	(4)	(5)
Pure Insider Sales	0.013	0.139**	−0.046	−0.069	−0.093
	(0.28)	(2.56)	(-1.11)	(-1.16)	(-1.11)
Tobin's Q	0.015	0.062**	0.010	−0.008	−0.009
	(1.04)	(2.44)	(0.60)	(-0.39)	(-0.38)
Log (Total Assets)	0.411***	0.409***	0.453***	0.351***	0.311***
	(6.42)	(3.98)	(5.92)	(4.27)	(2.75)
ROA	0.267	0.572	0.145	0.217**	0.091
	(1.39)	(1.58)	(0.94)	(1.98)	(0.62)
R&D/Total Assets	2.057***	2.191***	2.157***	1.858***	1.782***
	(5.14)	(3.34)	(5.47)	(3.70)	(3.14)
IO	−0.101	−0.536	−0.166	0.011	−0.006
	(-0.63)	(-1.37)	(-0.94)	(0.04)	(-0.02)
Illiquidity	−0.083***	−0.096**	−0.099***	−0.079**	−0.097*
	(-3.20)	(-2.36)	(-3.18)	(-2.04)	(-1.71)
Stock Returns	0.058**	0.038	0.068**	0.075***	0.090**
	(2.46)	(0.86)	(2.35)	(2.64)	(2.26)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.894	0.845	0.894	0.770	0.706
# of Firm-Year Obs.	16,764	12,692	16,038	11,875	9,461
# of Unique Firms	1,353	963	1,257	906	699

This table depicts the relationship between pure insider sales and future firm innovation using the following Poisson regressions $ln(Innovation_{i,t+1}) = \beta_0 + \beta_1 PureInsiderSale_{i,t} + \gamma Z_{i,t} + Firmfixedeffects + Yearfixedeffects + \in_{i,t+1}$.
The dependent variable is innovation productivity for firm *i* in year *t* + 1, measured in term of the number of patents of varying quality applied during the year. *Total Patents* is the total number of patents. *Loser Patents* is the number of patents that receive no future citations. *Intermediate Patents* is the number of patents that are neither loser patents nor top 10 % patents as defined below. *Top 10 % Patents* (*Top 5 % Patents*) is the number of patents that fall among the top 10 % (top 5 %) of their technological class and year in terms of future citations. The key explanatory variable is *Pure Insider Sales*, a dummy variable that takes the value of one if there is at least one insider sale in year *t* and *t*-1 without an insider purchase, and zero otherwise. The vector of *Z* firm-level controls includes the following. *Tobin's Q* is the ratio of book value of assets minus book value of equity plus market value of equity to the book value of total assets. *ROA* is the return on assets. *R&D/Total Assets* is R&D expenditure divided by total assets. *IO* is the institutional ownership measured at the end of the year. *Illiquidity* is Amihud's measure of illiquidity for the year. *Stock Returns* is the annual stock return. The sample period is 1988–2008. The *z*-statistics reported in parentheses are based on robust standard errors that are clustered at the level of both firm and year. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Chairman of the Board, Officer/Director holding more than 10 % of a class of share) sell shares in the company for two successive years without a purchase. In Column (1), where the dependent variable is total patents, the coefficient estimate on *Pure Insider Sales* is insignificant. In Columns (2) through (5), where the dependent variable is separated based on the patents' quality, we notice some interesting results. The coefficient estimates on *Pure Insider Sales* decrease monotonically as we move from low to high quality patents, though we only observe a statistically significant coefficient for the failed patents in Column (2). The positive coefficient estimate of 0.139 (z-statistic = 2.56) in Column (2) indicates that insider sales increase prior to the filing of failed patents, consistent with insiders selling their shares when they expect a deterioration of the firm's innovation performance in the near future.

5. Abnormal stock returns associated with insider purchases that precede important innovation

The benefits of breakthrough patents can be enormous and accrue over a long time because they tend to be an indication that firm has developed strategic assets (Ahuja et al., 2005). They impact future economic performance and serve as isolating mechanisms to keep technologies from rivals or allow firms to capture rents through licensing. They also signify underlying tacit and complex knowledge critical to subsequent innovations or to commercialization. Breakthrough patents can, therefore, have a significant impact on firm value. To the extent that insiders purchase shares in anticipation of breakthrough patents, such purchases are therefore likely to be associated with large positive returns in the future.

This section, therefore, attempts to quantify the abnormal stock returns associated with insider purchases that precede breakthrough patents. As before, we define such patents as those that fall in the top 10 % of the distribution of all patents in the same technology class and year. From these patents, we filter out those that are preceded by pure insider purchases. For each of these patents, we identify the last insider purchase that takes place in the year preceding the filing of the patent and compute the abnormal returns for the stock over a 36-month window beginning with the month following the insider purchase. Fig. 1 clarifies the timeline. The firm files for one or more breakthrough patents in year t + 1, and pure insider purchases take place in years t and t-1. For each breakthrough patent, we identify the last insider purchase, which takes place sometime during year t. We then track abnormal stock returns over a 36-month window that begins with the month following the month of the trade. To see if there is a pattern across times in how the returns accumulate, we break our 36-month return window into four overlapping periods. We first look at the stock returns in the calendar month following the insider purchase. For much of our sample period, this is the month in which the information about the insider trade becomes public.[15] So, this shorter return window may be viewed as the "announcement month" return window. We then examine the returns over 3-,6- and 36-month windows, beginning with the month of the announcement, in order to examine the medium and long-term returns associated with insider purchases.

To obtain estimates of average abnormal stock returns for each return window, we employ the calendar time portfolio approach and estimate the Fama and French (1993) three factor regressions. Following prior studies (Ritter and Welch, 2002; Chemmanur and Paeglis, 2005), we include the lagged values of the factors in the regressions. The estimates of intercepts are measures of monthly abnormal returns, with positive intercepts indicating overperformance. The regressions are estimated separately for each return windows based on the respective monthly time series of raw returns. To obtain these time series, for each month, we form portfolios that include stocks that experienced insider purchase in the preceding 1, 3, 6 or 36 months, respectively. Equally weighted returns on these portfolios for each month yield us the monthly time series of raw returns for a particular return window. Because the number of stocks in the monthly portfolios tends to be small for some months, especially for the one-month return window, we follow Chemmanur and Paeglis (2005) and estimate the Fama-French three-factor regressions using weighted least squares with the weights based on the number of stocks in the monthly portfolio.

Table 7 reports the results of the analysis. The abnormal returns during the one-month window, which depicts the calendar month in which the information about insider purchases becomes public, is positive at 1.9 % (t-statistic = 1.87). The positive return in the announcement month is consistent with prior studies (Sehyun, 1998). Over the three-month window, the return weakens and becomes statistically insignificant at 0.7 % (t-statistic = 1.01). However, over longer windows of 6-months and 36-months, the monthly average returns again become reliably positive. For the 36 month window, the insider purchases earn an average return of 1.1 % per month (t-statistic = 2.82). This translates into an annualized return of 14 %. In the long-term, therefore, insider purchases before important innovations earn large positive abnormal returns.

The timing over which the returns to insider purchases accrue is interesting indeed. While the initial positive abnormal returns in the announcement month are not surprising, the fact that the return tapers off in the subsequent three months before picking up in the later period is consistent with the long-term nature of the insiders' information advantage with respect to firm innovation. As noted earlier, innovation is a long-drawn process. The insider purchases we examine take place in the year preceding the filing of the patent application, when innovation process has matured but has not yet been put through the regulatory approval phase. After the filing of the patent, it takes about two and half years on average before

[15] Until 2002, the reporting requirements were governed by Section 16(a) of the Securities and Exchange Act of 1934. It required that insider transactions be disclosed within the first 10 days of the month following the month of the trade. However, the Sarbanes–Oxley Act of 2002, which became effective on Aug. 29, 2002, modified this requirement. The new reporting requirement states that insider transactions must be reported electronically by the end of the second business day following the day on which the transaction is executed both through the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) site and corporate public Web sites.

Table 7
Future stock returns from insider purchases before breakthrough patents.

Variables	1 month	3 months	6 months	36 months
	(1)	(2)	(3)	(4)
Intercept	0.019*	0.007	0.011*	0.011***
	(1.87)	(1.01)	(1.90)	(2.82)
$(R_{m,t} - R_{f,t})$	1.690***	1.224***	1.200***	1.277***
	(7.24)	(7.66)	(9.40)	(14.53)
$(R_{m,t-1} - R_{f,t-1})$	0.455*	0.293*	0.228*	0.020
	(1.87)	(1.85)	(1.73)	(0.22)
SMB_t	1.033***	0.915***	0.978***	1.154***
	(3.66)	(4.65)	(5.98)	(10.36)
SMB_{t-1}	0.044	0.191	0.252	0.184*
	(0.16)	(0.98)	(1.56)	(1.69)
HML_t	0.526	−0.183	−0.187	0.015
	(1.49)	(-0.80)	(-0.98)	(0.12)
HML_{t-1}	−0.093	0.250	0.251	−0.003
	(-0.26)	(1.13)	(1.36)	(-0.03)
# of Months	140	165	174	211
Avg. No. of Stocks Per Month	5	12	23	108
R-squared	0.40	0.44	0.538	0.69

This table reports future abnormal stock returns associated with the individual pure insider purchases that precede the firm's application for breakthrough patents. We define breakthrough patents as those that fall among the top 10 % in terms of future citations relative to all other patents in the same technology class and year. Pure insider purchases are defined as before—purchases that take place over two consecutive years without any corresponding insider sale. We follow the standard calendar time portfolio approach in which intercepts from Fama–French factor model regressions depict the monthly abnormal stock returns. $R_{pt} - R_{ft} = Intercept + \beta_1(R_{m,t} - R_{f,t}) + \beta_2(R_{m,t-1} - R_{f,t-1}) + \beta_3 SMB_t + \beta_4 SMB_{t-1} + \beta_5 HML_t + \beta_6 HML_{t-1} + \epsilon_{p,t}$.
The subscripts *p* and *t* depict portfolio and month, respectively. The dependent variable in the first column is the return in excess of risk free rate on an equally-weighted portfolio of firms that experience at least one pure insider purchase in the preceding month. Likewise, the dependent variables in Columns (2) through (4) are the excess return on equally-weighted portfolio of firms that experience at least one pure insider purchase in the previous 3, 6 and 36 months, respectively. The regressions are estimated using weighted least squares, with the weights based on the number of firms included in the portfolio each month. $(R_m - R_f)$ is the realization of the market risk premium. *SMB* is the return on a portfolio of small stocks minus the return on a portfolio of big stocks. *HML* is the return on a portfolio of high book-to-market stocks minus the return on a portfolio of low book-to-market stocks. *, **, and *** indicate statistical significance at the 10 %, 5 % and 1 % levels, respectively.

the patent is granted. Throughout this long approval period, outside investors can gradually learn more about the innovation (KPSS). The realization of abnormal stock returns over this long period can give insiders a greater chance to skip legal scrutiny envisioned in Section 16(b) of the Securities and Exchange Act of 1934. The results in Table 7 suggest that insiders who purchase before important firm innovation need not close their trades within the 6-month blackout period envisioned in Section 16(b). They can do so over a much longer period. Greater long-term returns, therefore, make insider purchases grounded in innovation information distinct from insider trading based on other events such as earnings announcements whose returns accrue over shorter windows and which therefore could be more susceptible to legal scrutiny.

It is instructive to note that our analysis in this section suffers from look-ahead bias. The insider purchases for which we examine future stock returns do not represent the full universe of insider purchases; they represent a subset chosen retrospectively based on the information about the subsequent filing of the important patents. So, it is not surprising if they generate positive abnormal returns. Yet we believe our analysis is interesting because it quantifies the large magnitude of the returns and more importantly because it reveals the long duration of the time over which these returns accrue.

6. Prior insider purchases and the stock returns around the announcements of the grant of patents

Because the underlying motives for insider trades are not usually publicly known, it is challenging for researchers to label any insider trading as opportunistic and link it reliably to specific private information. This has been a limitation of most studies on insider trading and our work is no exception. However, we attempt to partly address this issue in this section. We rely on the commonly accepted notion that insider trading results in the assimilation of managerial private information into stock prices (see, for example, Meulbroek, 1992; Massa et al., 2015).[16] If insider purchases that we study are indeed motivated by private information about future success of firm innovation, these purchases would facilitate incorporation of some of this information into stock prices, resulting in lower stock price reaction when the information is subsequently made public.

The recent work of KPSS helps facilitate testing of this prediction. They argue that the information about the success of a firm's innovation becomes public primarily when USPTO announces the successful outcome the firm's application for patent by granting the patent to the firm. Based on this argument, they compute the market value of each patent by looking at the abnormal stock returns in the three days surrounding the announcement of the grant of the patent. The data on these market

[16] Meulbrouk (1992) uses data on illegal insider trading from the Securities and Exchange Commission and documents that the stock market detects the possibility of informed trading and impounds this information into the stock price. Massa et al. 2015) find that insiders attempt to trade ahead of short sellers and help speed up incorporation of bad news into stock prices.

Table 8
Prior insider purchases and the stock returns around the announcements of the grant of patents.

Explanatory variables	Dependent variable = patent value
Pure Insider Purchases	−45.70*
	(-1.73)
ln (1 + Citations)	30.47**
	(2.77)
Tobin's Q	36.59***
	(3.64)
ln (Total Assets)	122.89***
	(3.80)
ROA	15.36
	(0.36)
R&D/Total Assets	96.15
	(0.97)
IO	−280.48**
	(-2.10)
Illiquidity	−1.33
	(-0.14)
Stock Returns	3.27
	(0.24)
Firm FE	Yes
Year FE	Yes
R-squared	0.791
# of Firm-Year Obs.	20,205
# of Unique Firms	1,741

This table investigates whether prior insider trading attenuates stock market reaction to the announcement of the grant of patents, using the following OLS regression $PatentValue_{j,i,d,t+1} = \beta_0 + \beta_1 PureInsiderPurchase_{i,t-2} + \beta_2 \ln(1 + Citations_{j,i}) + \gamma Z_{i,t} + Firmfixedeffects + Yearfixedeffects + \in_{j,i,d,t+1}$.
The subscripts *j*,*i*,*d* and *t* signify patent, firm, the date of the announcement, and the year of the announcement respectively. The dependent variable, *Patent Value*, is the stock market reaction to the announcement of the grant of a patent. We obtain the data for it from KPSS, who computes it as the increase in a firm's stock market capitalization (in millions of dollars) around the announcement. The key explanatory variable, *Pure Insider Purchases*, is an indicator variable that takes the value of one if there is at least one insider purchase, without any insider sales, over two consecutive years preceding the application of the patent, which are typically year/t^{-2}(−|-) and *t*-3. *Citations* is the number of future citations received by the patent. *Tobin's Q* is the ratio of book value of assets minus book value of equity plus market value of equity to the book value of total assets. *ROA* is the return on assets. *R&D/Total Assets* is R&D expenditure divided by total assets. *IO* is the institutional ownership. *Illiquidity* is Amihud's measure of illiquidity for the year. *Stock Returns* is the annual stock return. All firm-level controls are lagged by one year. The *t*-statistics reported in parentheses are based on robust standard errors that are clustered at the level of both firm and year. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

value estimates has been made available on the Internet.[17] After merging this information with our dataset, we regress the market value estimates on our indicator variable, *Pure Insider Purchases*, and controls. If insider purchases help speed up the release of information about patents to the market in the pre-grant period, we expect the coefficient on *Pure Insider Purchases* to be negative. As clarified in Fig. 1, the time of the announcement of the grant of patent by USPTO would typically, though not always, fall outside of the 36-month return window associated with the insider trade we examine in the previous section. Whereas insider trade takes place during year *t*, the patent would typically be granted afterwards in year *t* + 3 and year *t* + 4.

Table 8 reports the results. The estimated coefficient on *Pure Insider Purchases* is −45.7 (*t*-statistic = 1.73). Because the dependent variable of the value of the patent is measured in millions of dollars, this coefficient estimate indicates that pure insider purchases, on average, result in a reduction in the stock market response to the announcement of patent grant by $45.7 million. Given the mean and standard deviation of $344 million and $1,578 million, respectively (reported in Table 1), the point estimate of $45.7 million seems economically large. The results therefore indicate that stock prices react less to the announcements of the grant of patents when these announcements are preceded by insider purchases. This is consistent with the idea that these insider purchases are motivated by private information about future innovation and help facilitate early incorporation of this information into stock prices.

The coefficient estimates on the control variables in Table 8 are also instructive and in line with prior evidence. The coefficient on the alternative measure of the (scientific) value of the patent—the number of future citations the patent gets—is positive and statistically highly significant. This is consistent with the findings of KPSS who show that their stock-price-reaction-based measure is strongly correlated with the citations-based measure of the value of a patent. Even though the inclusion of this variable in the regression introduces look-ahead bias—the information about future citations may not be fully known at the time of the grant of patent—we include it so that we can assess the stock price response after controlling for the quality of the patent, which is likely to be an important driver of stock price response. As noted earlier, future citations is the most prominent measure of scientific quality of a patent identified in the innovation literature. Our result, however, remains robust to the exclusion of this variable from regression. The coefficients on the firm size and Tobin's Q also show up as positive, consistent with the idea that larger firms and those with better growth options are better able to internalize the benefits of their innovation (KPSS).

[17] We thank Noah Stoffman for making these data available on his web site.

Table 9
The Effect of Governance on the Relationship between Insider Trading and Future Firm Innovation.

	Dependent variable = Total Patents	
Explanatory Variables	With Blockholders	Without Blockholders
Pure Insider Purchases	0.057	0.187**
	(1.21)	(2.21)
Tobin's Q	0.007	0.032*
	(0.42)	(1.94)
ln (Total Assets)	0.514***	0.336***
	(5.19)	(4.48)
ROA	0.333	0.269
	(1.05)	(1.38)
R&D/Total Assets	1.944***	1.641***
	(4.38)	(3.82)
IO	−0.140	−0.071
	(-0.80)	(-0.31)
Illiquidity	−0.070**	−0.072**
	(-2.27)	(-2.39)
Return	0.030	0.067**
	(1.20)	(2.33)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Pseudo R-squared	0.864	0.933
# of Firm-Year Obs.	10,759	8,333
# of Unique Firms	1,155	1,084

This table reports the relationship between insider purchases and future firm innovation separately for sub-samples of firms with and without institutional blockholding. We first classify the firm-year observations into two groups based on the indicator variable *Institutional Blockholder,* which equals one if the firm has at least one institutional blockholder that owns at least 10 % of the outstanding shares, and zero otherwise. We then estimate the following Poisson regressions separately for each group. $ln(TotalPatents_{i,t+1}) = \beta_0 + \beta_1 PureInsiderPurchase_{i,t} + \gamma Z_{i,t} + Firmfixedeffects + Yearfixedeffects + \in_{i,t+1}$.
The dependent variable is innovation productivity for firm *i* in year *t* + 1, measured in term of the total number of patents applied by the firm during the year. The key explanatory variable, *Pure Insider Purchases*, is an indicator variable that takes the value of one if there is at least one insider purchase in year *t* and *t*-1, without an insider sale. *Citations* is the number of future citations received by the patent. *Tobin's Q* is the ratio of book value of assets minus book value of equity plus market value of equity to the book value of total assets. *ROA* is the return on assets. *R&D/Total Assets* is R&D expenditure divided by total assets. *IO* is the institutional ownership. *Illiquidity* is Amihud's measure of illiquidity for the year. *Stock Returns* is the annual stock return. All firm-level controls are lagged by one year. The *z*-statistics reported in parentheses are based on robust standard errors that are clustered at the level of both firm and year. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Even though we interpret the evidence in Table 8 as supporting our inference that insider purchases we study are motivated by information about future firm innovation, the results have broader implications for the innovation literature. An issue that has been central to this literature is how one can determine the economic value of a firm's innovation. In recent decades, it has been common to use future citations associated with a patent as an estimate of its *scientific* value. Hall et al. (2005) provide empirical support for this measure.[18] By aggregating citations-based value of all patents a firm generates, they compute an estimate of the overall value of the firm's total innovation in a given period and show that this value is positively correlated with the firm's market value. KPSS, however, argue that *scientific* value can diverge from the *private* value of a patent for the patenting firm because the firm may not be able to capture all of the benefits of its innovation. They propose their market value estimate as an alternative measure to compute the latter. Researchers are increasingly using these market value estimates to correlate firm innovation with other variables of interest (see, for example, Islam and Zein, 2020). However, as KPSS note, their estimate of the market value of a patent depends critically on the assumption that the information about the patent becomes known to the market at the time of the grant of the patents. To the extent that part of the information is disseminated to the market earlier, the abnormal stock returns around the grant would underestimate the patent value. Our evidence that insider trading helps assimilate some of the information about firm innovation before the grant of the patents suggests that the market-value estimates of KPSS are likely to be underestimated for those patents for which insiders trade beforehand.

7. Does better monitoring by shareholders weaken the association between insider trading and firm Innovation?

In our final analysis, we ask whether the predictability of insider purchases for future firm innovation weakens for firms that have better monitoring mechanisms in place. To the extent that insider purchases before important firm innovation represent insiders' opportunistic rent-seeking behavior, one might expect that such behavior is mitigated in the presence of a better monitoring mechanism. Prior work however finds that the usual proxies of better corporate governance, such as institutional ownership and the presence of independent directors on the board—have little explanatory power for the profitability of insider trading (see, for example, Dai et al., 2016). We therefore employ the presence of a large outsider blockholder as

[18] Several later studies also document a positive relation between citations-based measures and the market value of a firm (Nicholas, 2008; Harhoff et al., 1999; Moser et al., 2011).

Table 10
Appendix: variable definitions and data sources.

Variable	Description
Citations	Total number of future citations, excluding self-citations, received by the patents that a firm applies for in a given year. The citation count for each patent is corrected for truncation bias by dividing the count by the average number of citations received in the same two-digit technological field in the same application year. (Source: 2010 version of NBER patent data compiled by KPSS)
HML	Monthly time series of the return on a portfolio of high book-to-market stocks minus the return on a portfolio of low book-to-market stocks. (WRDS)
Illiquidity	Illiquidity is Amihud's measure of illiquidity for the year. (CRSP Daily Stock File)
Institutional Blockholder	A dummy variable that equals one for the years when an institution holds 10 % or more of all the outstanding shares. (Thomson Reuters Institutional Holdings)
Intermediate Patents	The number of patent applications that are neither loser patents nor top 10 % patents as defined above (Source: 2010 version of NBER patent data compiled by KPSS)
IO	Institutional ownership measured at the end of the year. (Thomson Reuters 13F dataset).
Pure Insider Purchases	A dummy variable that takes the value of one if there is at least one insider purchase in the current as well as the preceding year without an insider sale, and zero otherwise. Insiders include CEO, CFO, CO, President, Chairman of the Board or Officer/Director holding more than ten percent of a class of share. (Thomson Reuters Insider Filings Database)
Pure Insider Sales	A dummy variable that takes the value of one if there is at least one insider sale in the current as well as the preceding year without an insider purchase, and zero otherwise. Insiders include CEO, CFO, CO, President, Chairman of the Board or Officer/Director holding more than ten percent of a class of share. (Thomson Reuters Insider Filings Database)
R&D /Total Assets	Research and development expenses divided by Total Assets. (Compustat)
$R_m - R_f$	Market risk premium, which is one of the three Fama-French (1993) factors. (Monthly time series data are obtained from WRDS)
ROA	Return on Assets: Computed as EBITDA (earnings before interest, taxes, depreciation and amortization) divided by Total Assets. (Compustat)
SMB	Monthly time series of the return on a portfolio of small stocks minus the return on a portfolio of big stocks. (WRDS)
Stock Returns	Holding period stock return excluding dividends and adjusted for stock splits. (CRSP)
Tobin's Q	The ratio of book value of assets (Compustat data6) minus book value of equity (data60) plus market value of equity (Compustat data25*Compustat data199) to the book value of total assets (data6). (Compustat)
Top 10 % Patents	The number of patents filed by a firm in a given year that fall in the top 10 % of the distribution of future citations in the same technological field. Self-citations are excluded. (Source: 2010 version of NBER patent data compiled by KPSS)
Top 5 % Patents	The number of patent applications filed by a firm in a given year that fall in the top 5 % of the distribution of future citations in the same technological field. Self-citations are excluded. (Source: 2010 version of NBER patent data compiled by KPSS)
Total Assets	The book value of the total assets of a firm. (Compustat)
Total Patents	The number of patents applications filed by a firm in a given year that were subsequently granted. We correct for the well-known truncation problem in patent counts by using the truncation correction weights that are calculated from the application-grant lag distributions as described in Hall, Jaffe, and Trajtenberg (2001). (Source: 2010 version of NBER patent data compiled by KPSS)

This appendix provides the definitions of the variables used in the study. The source of the data for each variable is provided in parenthesis following its definition.

our proxy for a better monitoring mechanism that may constrain profitable insider purchases before innovations are announced. Shleifer and Vishny (1986) suggest that institutions that hold large blocks of shares in a firm may alleviate moral hazard problems through better monitoring. Cheng et al. (2007) employ institutional blockholding as a proxy for better monitoring of insider trading and find that the negative association between delayed Form-5 sales by insiders and the future stock performance is weaker for firms with large institutional blockholders.

To examine the impact of blockholder ownership on the association between insider purchases and firm innovation, we obtain information about the institutions that hold 10 % or more of the outstanding shares of a company from Thomson Reuters Institutional Holdings dataset. We then classify the firm-year observations in our dataset into those that have at least one institutional blockholder and those that do not. About 56 % (44 %) of the firm-year observations in our sample are classified in the former (latter) category.

Table 9 reports our baseline regressions separately for the firms with and without institutional blockholders. For firms with institutional blockholders, the coefficient estimate on *Pure Insider Purchases* is statistically indistinguishable from zero. In contrast, the corresponding coefficient for firms without institutional blockholders is about three times larger in magnitude and remains statistically significant. The predictability of insider purchases for future firm innovation therefore seems to be weaker for firms with institutional blockholders, consistent with the idea that monitoring by large blockholders mitigates the rent-seeking behavior of corporate insiders. Table 10.

8. Conclusion

The necessity of keeping innovation progress a secret in order to maintain competitive advantage against competitors enables insiders to possess a lot of private information and results in considerable information gap with outsiders. Because innovation is a long, drawn-out process, the information asymmetry between insiders and outsiders also likely lasts longer than that associated with other corporate events. This can provide insiders a convenient opportunity to gain profits from their purchases or/and prevent losses through sales.

This study provides an initial examination of the insider trading that precedes innovation-related activities of publicly held US firms. The results indicate that insider trades predict future important patents. The association between insider trading and future patents strengthens with the patent quality; insider purchases are especially useful in predicting the patents of the highest quality. Conversely, sales by top executives also predict deteriorating future innovation performance. Further analysis of insider purchases shows that insiders earn significant positive abnormal returns on their purchases prior to the important patent applications. These abnormal returns are large and accrue over an extended period of three years following the purchase. We also find that the association between insider trading and future firm innovation weakens for firms with large institutional blockholders.

We highlight at least three implications of our study. First, by directly linking insider trading with firm innovation, our results speak to the issue of the sharing of gains from innovation between entrepreneurs and financiers. We show that in publicly listed firms, managers can use opportunistic insider trading to capture a larger share of the gains from firm innovation than allowed through formal contracts. Second, our evidence that abnormal stock returns for insider purchases accrue over a long period before important firm innovations become publicly known calls into question the efficacy of the six-month trading embargo before corporate events envisioned in Section 16(b) of the Securities and Exchange Act of 1934. Because the information advantage associated with innovation can last for a longer period among technology firms, our study suggests the need for a re-examination of the length of the embargo period. The importance of this is further underlined by the increasing dominance of technology firms in the US stock market. Finally, our results serve as a caution to researchers in the innovation literature who are increasingly assigning a market value to patents based on stock price reaction to the announcement of the grant of a patent. We show that these market value estimates are likely to underestimate the true market value for those patents that are preceded by pure insider purchases.

Data availability

The data that has been used is confidential.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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