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Intellectual Property News and Informed Trading: Evidence from Patenting Activities

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Abstract

Using newly developed informed trading measures as well as updated patent-related data, we provide evidence that informed trading increases in the quarter during which firms are granted more, better-quality, and higher-valued patents. Patent news also predicts informed trading up to two quarters ahead, suggesting that it takes time for the stock market to fully reflect such information. Our results are robust to a series of tests. We find that the trading behavior of transient institutional investors is the main driver of the relations. In addition, we provide evidence that investors interpret patent-related news to a focal firm as bad news to its rival firms and trade their shares accordingly. But the cross-firm effects occur only in the current period.

***JEL Classification*:** G14, G12, O31

***Keywords*:** Information Asymmetry; Informed Trading; Price Impact, Order Imbalance; Conditional Probability of Informed Trading; Corporate Innovation; Patenting Activities; Product Similarity Scores; Cross-Firm Effects in Rival Firms

1. Introduction

The U.S. Patent and Trademark Office (USPTO) publishes the *Official Gazette* on Tuesdays to inform the general public of approved patents and related documents that include their technical details. Although the information about a newly granted patent(s) is publicly announced, it is likely that only some of market participants ("informed traders" or "informed investors") analyze the technological details of the patent(s) granted to a firm and interpret the implications of it, because most of them do not have adequate expertise or resources to collect and process information about the new intellectual property. Given the complexity and uncertainty of technological inventions, sophisticated investors with knowledge and experience in technologies have advantages over the rest of the general public. Therefore, patent news causes information asymmetry among market participants. This would motivate some skilled investors to exploit their advantage by trading on such news.

In today's knowledge-based economies, the success of a firm is largely determined by its innovating activities (Scherer, 1965, 1967; Griliches, 1981; Hall, 1993). The literature has thus presented abundant empirical evidence on the positive effect of firm-level innovation performance on accounting profitability (Pandit, Wasley, and Zach, 2011) as well as on stock returns (Deng, Lev, and Narin, 1999; Gu, 2005; Pandit, Wasley, and Zach, 2011; Cohen, Diether, and Malloy, 2013; Hirshleifer, Hsu, and Li, 2013). In contrast, little is known about the channel through which patenting activities of individual firms are reflected in stock prices. We expect that knowledge and skill differences result in information asymmetry, providing an opportunity for some investors to capitalize on their informational advantage, which in turn leads to trading activities in financial markets (Chordia, Huh, and Subrahmanyam, 2007). All these aspects suggest that there is a positive link between patenting activities and informed trading.

Brennan, Huh, and Subrahmanyam (2016b) provide evidence that informed trading occurs not only *before* but also *after* announcements of corporate events (e.g., earnings or M&A announcements). This lends support to models such as Kim and Verrecchia (1994, 1997) in which different agents have different interpretations of public information signals, or models in which different agents have different abilities to process the information from *public* announcements. Given the public news announced by the USPTO, it is very plausible that market participants look for data on patenting activities, produce useful information, interpret the implications of such information for future cash flows in the firm, and eventually reveal the information through trading activities in shares of the firm. In doing so, some investors would be more active in the process than other investors, depending on the level of their skills and expertise. Considering the importance of corporate innovation, we expect that patenting performance of a firm may affect trading activities in its rival firms as well.

Although anecdotal evidence has indicated that investors in financial markets trade securities based on innovation news, there is no empirical research in the literature regarding the impact of corporate innovation on informed trading in shares of the innovating firms or their rival firms.[1] Admittedly, testing the relations between innovating activities and trading on such information is challenging, partly because of difficulties in estimating appropriate measures of information asymmetry or informed trading that are of reasonably high frequency and difficulties in constructing proper measures of corporate innovation. Fortunately, some reliable measures of informed trading and patenting activities have recently become available. This allows us to conduct empirical study on the issues described above.

Our goal in this study is threefold. First, by constructing relevant measures of informed trading and corporate innovation, we test whether in practice investors track patenting activities and trade on such public news. Second, if market participants do react to the patent-related news, we attempt to answer the question of specifically who is most active in trading on such information. Third, given that obtaining patent approvals or citations is good news for a firm, is there any cross-firm effect on trading in its rival firms? This is an interesting issue to explore, because good news for the firm can be interpreted as bad news for its competitors. Thus, informed investors who follow its rival firms may react to the news in a different manner. To the best of our knowledge, this study is the first research that focuses on the mechanism (i.e., trading) through which information on patenting activities is impounded in stock prices of innovating firms as well as of their rival firms.

For this study, we construct two high-frequency-based informed trading proxies. The first measure of informed trading (denoted by Ω) is computed as price impact times order imbalance. Considering that order imbalance reflects information shocks and price impact is the component of trading costs caused by adverse selection, Ω is an intuitive measure for informed trading that incorporates *both* price impact and order imbalance. Given that patent approvals by the USPTO

[1]Informed trading emanates from agents other than insiders. Vega (2006) makes a similar argument, "...is not exclusively an insider trading measure as it also captures informed trading by investors who are particularly skillful in analyzing public news." Our study focuses on informed trading on *public* information (after announcements), as opposed to informed trading on *private* information (i.e., 'insider' trading before announcements).

are good news for awarded firms, we employ another measure (denoted by Π_g) which is the conditional probability of informed trading on good news developed by Brennan, Huh, and Subrahmanyam (2016b). As Brennan, Huh, and Subrahmanyam (2016a, 2016b) point out, a significant limitation of informed-trading measures used in prior studies is the long estimation window and low frequency (annual), which make those measures fail to reflect time-varying features in informed trading around corporate events. Therefore, we estimate both measures at a higher frequency to ensure that our measures can capture variation in informed trading around corporate events more efficiently and yield more powerful test results.

We also use measures related to intellectual property news that reflect the performance of innovation activities and their economic value. Using the Harvard Business School patent inventor data (Li et al., 2014), we construct two patent-based proxies for firm-level innovation performance: the number of each firm's patents granted by the USPTO in each quarter, and the total number of citations that are received by the patents granted to a firm, each of which 'directly' captures the patenting performance of the firm in terms of quantity and quality, respectively. Given the data availability, the sample period in this study is limited to the 1990-2010 period. Following Bena and Li (2014), we adjust the above two variables, which are respectively denoted by $ANPAT$ (the adjusted number of patent counts) and $ANCITE$ (the adjusted number of patent citations), to correct for the heterogeneity across industries in their patenting activities as well as in the influence of their granted patents. Since patent owners are required to disclose the details of their inventions in the *Official Gazette*, the information related to granted patents is open to all investors. The sample for our main analyses includes only the firms that have positive values in the number of granted patents over the past 84 quarters (1990:Q1-2010:Q4) for NYSE/AMEX-listed firms, although firms with no granted patents are also included for robustness checks.

To capture the economic value of intellectual property associated with granted patents, we employ the measure used in Kogan et al. (2015), who compute the value of a patent based on stock price changes around the patent announcement date. Since market participants know who are the owners of patents and have access to their technical details, stock prices reflect their values accordingly around the announcement dates. Kogan et al. (2015) adjust the variable for aggregate market movements, idiosyncratic return volatility, firm-year fixed effects, and day-of-week fixed effects. Thus, their method provides us with market-value-based (hence, 'indirect') estimates of innovating activities (denoted by $AVAL$).

A portfolio analysis shows that our two informed trading measures are monotonically increasing in patenting activities proxied by the three measures. We next conduct regression analyses to investigate in a multivariate setting whether investors engage in informed trading based on the news about corporate innovation. The results from cross-sectional and pooled regressions show that informed trading increases significantly with the three innovation proxies in the quarter during which firms obtain patent approvals. While the contemporaneous effect is largest, we observe that the three innovation measures also predict informed trading up to two quarters ahead.[2] This strongly suggests that, concurrently as well as with some time lags, informed investors buy stocks of firms that acquire more, better-quality, and higher-valued patents. The fact that innovation performance predicts informed trading up to two quarters also implies that it takes time before some investors react to publicly available information.

Our empirical results are little affected when we control for R&D intensity, changes in insider holdings, and other variables that are known to explain information asymmetry, including the lagged dependent variable (one of the two informed trading measures) as well as the industry and year fixed effects in the pooled regressions. The results are robust to using alternative proxies for informed trading and to extending the sample so that it includes the firms with no granted patents. The above findings altogether support the notion that patent-related news is indeed an important determinant and predictor of informed trading in securities markets.

As for the industry effects, our analyses show that the telecom industry accounts for the lion's share of granted patents and citations. Therefore, the telecom industry is highly subject to informed trading. Firms in the business equipment industry obtain relatively large numbers of patents and citations, and we find that the industry also has more room for informed trading. On the other hand, consumer non-durables, durables, and wholesale/retail industries are less vulnerable to informed trading, relative to the base ('Other') industry.

We note the possibility that our empirical results are vulnerable to endogeneity. To address this issue, we first run difference-in-differences (DiD) regressions around the 1998 policy shock (a court ruling on the "State Street vs. Signature Financial Group" case). According to Hall (2009), the court decision strengthened the protection of patents related to business methods and algorithms, substantially increasing the value of patents in the finance and business equipment industries. Our analyses show that patent news induces more intensive informed trading

[2] Ali, Durtschi, Lev, and Trombley (2004) find that institutional investors trade on information up to two quarters after the earnings announcement date.

in the affected firms after the court decision. Our second identification strategy is to implement two-stage least squares (2SLS) regressions by devising two instrumental variables: the average time taken from patent application to its approval, and the innovation performance in the past. In the first stage of the estimation, we find that the first instrument negatively affects patenting activities while the second one positively do so. The second-stage estimation results show that informed trading significantly increases with the fitted innovation variables, which are estimated from the first-stage regressions and thus purged of all firm-level omitted variables. In summary, the DiD and 2SLS regression results collectively support our causal interpretation between patent-related news and informed trading.

Next, we explore specifically who is more active in exploiting innovation-related information. To examine this issue, we construct portfolios by sorting component firms on the change in the ownership of short-term institutional investors, and then conduct regressions for firms in the top and bottom quartiles. This result suggests that the effect of intellectual property news on informed trading is more pronounced when short-term (or transient) institutional investors react aggressively to the patent-related information. In another experiment, we sort the firms on the correlation between the change in the number of granted patents and the change in short-term institutional ownership in previous quarters. We find that the effect of patent performance on informed trading is stronger in the current period when short-term institutional investors reacted more positively to patent-related information in the past. These findings confirm that the trading behavior of aggressive transient institutional investors is the main driver of the causal relations between patent-related news and informed trading.

Lastly, after selecting the nearest rival firms [based on the Hoberg-Phillips (2010, 2016) product similarity scores] that acquire relatively fewer (or no) patents/citations in each quarter than a 'focal' firm does, we investigate how informed investors who follow its rival firms react to the news that the focal firm obtains patent approval(s) or citations. Our first test results show that for the rival firms our patent-news measure is not positively associated with either of the two informed trading measures (Ω or Π_g), demonstrating that the positive relations between patent news and informed trading observed in the focal firms are not by chance. In the second experiment, we test whether investors interpret the information as bad news, when patent-related (good) news arrives in a focal firm. For this test, we construct a conditional measure of informed selling on bad news, Π_b. The analyses show that the patent-news measure itself is not significantly associated with Π_b. However, when the patent-news measure is interacted with the indicator variable for rival firms, the coefficient on the interaction term becomes positively significant at the 1% level. This suggests that investors interpret the news that the focal firms obtain patent approvals/citations as bad news to the rival firms and trade on that information accordingly (i.e., sell or sell short shares of the rival firms). But we find that the cross-firm effects in the rival firms disappear after the current period.

The paper is organized as follows. In Sections 2, we describe data, construct relevant variables, and provide descriptive statistics. Section 3 presents the relation between corporate innovation and informed trading, together with robustness checks. In Section 4, we conduct further identification tests. In Section 5, we explore which investors actively trade on patent news. Section 6 provides evidence of cross-firm effects in rival firms. Section 7 concludes.

2. Variable Construction and Data

2.1. Measures of Informed Trading

The vast majority of studies that use informed-trading measures, such as PIN, estimate the measures at a low (annual) frequency (e.g., Easley, Hvidkjaer, and O'Hara, 2002; Aktas, de Bodt, Declerck, and Oppens, 2007; Mohanram and Rajgopal, 2009; Duarte and Young, 2009; Lai, Ng, and Zhang, 2014). However, Brennan, Huh, and Subrahmanyam (2016a) point out that a significant limitation of informed-trading measures used in finance and accounting studies is the long estimation window and low frequency, which makes them inefficient in capturing time-varying features of information asymmetry around corporate events and hence reduces the power of tests. In this study, therefore, we construct two high-frequency-based measures of informed trading using transaction-level databases.

2.1.1. Ω Constructed with Price Impact and Daily Order Imbalance

Price-impact parameters or price impact [often called "lambdas (λ's)"] measure the component of trading costs caused by adverse selection or information asymmetry. Prior studies show that price impact estimated using intradaily order flows commands a significant return premium (e.g., Chordia, Huh, Subrahmanyam, 2009; Huh, 2014; Chung and Huh, 2016). Other studies analyze the role of order imbalance as a proxy for informed trading in financial markets (e.g., Evans and Lyons, 2002; Brandt and Kavajecz, 2004; Green, 2004; Back, Crotty, and Li, 2015). Order imbalance (OIMB) occurs when a security is hit by news (public and private) related to earnings, merger and acquisition activities, or other important corporate events. Therefore, price impact and order imbalance have often been used independently as a proxy for information asymmetry or informed trading. But some studies such as Back, Crotty, and Li (2015) suggest that order flows alone may not be sufficient to capture information asymmetry.

We construct the first measure of informed trading with the two components: that is, price impact times order imbalance (i.e., λ*OIMB), which is denoted by Ω. Given that order imbalance reflects information shocks and price impact is the component of trading costs caused by adverse selection, it is intuitive to construct a measure that incorporates *both* price impact and order imbalance. Moreover, this measure has other advantages: it can be estimated at a high frequency and does not suffer from the 'overflow/underflow' problem in the estimation process; and it can also capture the direction of informed trading.

To construct this measure, we first process intradaily dollar-volume order flows. Processing order flows requires that each trade in ISSM/TAQ be signed as a buyer- or seller-initiated trade. To match trades and quotes and then classify each trade as buyer- or seller-initiated, we use the Lee and Ready (1991) algorithm for years up to 2006. Any quote less than five seconds prior to the trade is ignored and the first one at least five seconds prior to the trade is retained for the sample period from 1983 to 1998. Since the timing differences in recording trades and quotes were reduced in recent years, we impose the two-second-delay rule from 1999 to 2006. Given the prevalence of high-frequency trading in recent years, however, we classify each trade via the Holden and Jacobsen (2014) algorithm from 2007 to 2010.[3] The transactions data are then signed as follows. If a trade occurs above (below) the prevailing quote mid-point, it is classified as buyer-initiated (seller-initiated). To minimize possible signing errors in processing order flows, we discard the approximately 5% of the trades that occur exactly at the quote mid-point, following Sadka (2006).

Once each trade is classified as above, intradaily order flows are aggregated to obtain daily buys and sells [in trade numbers (denoted by B and S), in share volume (SB and SS), and in dollar volume ($\$B$ and $\$S$ in \$million)[4]]. Then the daily dollar-volume order imbalance

[3] The main points of the Holden-Jacobsen (2014) algorithm are: (i) adjustments for withdrawn quotes, (ii) time-interpolation during each one-second period, (iii) matching trades with national best bid and offer (NBBO) quotes across different exchanges, and (iv) excluding crossed or locked NBBOs.

[4] Note that, for example, intradaily buy-side volume in dollars ($\$B$) is the intradaily transaction price times

($DOIMB^D$) is calculated as the daily aggregated buyer-initiated dollar volume ($\$B$) minus the seller-initiated dollar volume ($\$S$). That is, $DOIMB^D = (\$B - \$S)$.

To estimate price impact (λ), we employ the Foster and Viswanathan (1993) model. This approach has an advantage compared to other models such as Glosten and Harris (1888), because the order-splitting practice in recent years may have caused order flows to be serially correlated. We filter order flows by the AR (5) process as in

$$K_{i,t,m}V_{i,t,m} = c + \sum_{k=1}^{5} \theta_k K_{i,t-k,m}V_{i,t-k,m} + \tau_{i,t,m},$$

where $K_{i,t,m}$ is the sign of a trade ($K = +1$ if the trade is buyer-initiated and $K = -1$ if it is seller-initiated) in stock i at intraday trade t in month m; $V_{i,t,m}$ is the dollar volume of the trade in \$million; $K_{i,t,m}V_{i,t,m}$ is signed dollar volume (i.e., intradaily dollar order flow); and $\tau_{i,t,m}$ is the residual from the time-series regression. We then use $\tau_{i,t,m}$ to estimate λ^{FV} as follows:

$$\Delta P_{i,t,m} = \overline{\varphi}^{FV}_{i,m}(K_{i,t,m} - K_{i,t-1,m}) + \lambda^{FV}_{i,m}\tau_{i,t,m} + \xi_{i,t,m}, \tag{1}$$

where $\Delta P_{i,t,m}$ is the change in the price of stock i at intraday trade t in month m, and $\xi_{i,t,m}$ is the unobservable error term. $\overline{\varphi}^{FV}$ is the non-information component of trading costs, and λ^{FV} is price impact or the adverse-selection component of trading costs. The parameters $\overline{\varphi}^{FV}$ and λ^{FV} are estimated each month for each stock by time-series regressions using all available intradaily order flows within the month.

Given the order imbalance and the price-impact parameter available, we compute the daily measure of informed trading, ω^D, as:

$$\omega^D = \lambda^{FV}_{m-1} * DOIMB^D, \tag{2}$$

where λ^{FV}_{m-1} is the monthly price-impact parameter estimated within the previous month (month $m-1$) and $DOIMB^D$ is the daily dollar-value order imbalance (in \$million) in the current month (month m).[5] In obtaining current month's daily measures, we use previous month's λ^{FV} to avoid a look-ahead bias. The monthly measure (ω^M) is the average of daily ω^D's within each

the share volume in the trade classified as buyer-initiated.

[5] About 2.5% of λ^{FV} estimates in the sample are negative, in which case λ^{FV} is set as zero.

month, and then we obtain Ω as the quarterly average of monthly ω^M's within each quarter.

2.1.2. π_g^Q and Π_g Constructed Using the Daily Conditional Probabilities of Informed Trading

Brennan, Huh, and Subrahmanyam (2016a) show that *PIN* and its two components estimated at a quarterly frequency based on the Easely, Kiefer, O'Hara, and Paperman (EKOP, 1996) model are superior to *AdjPIN* estimated based on the Duarte and Young (DY, 2009) model, and that the *PSOS* measure of DY does not efficiently separate out illiquidity component unrelated to information asymmetry from *PIN*.

In the EKOP model, one of three possible events occurs each day. That is, there is no news about the stock (with probability ϕ), there is good news (with probability g), or there is bad news (with probability b). In their model, the unconditional probabilities of these events can be written as $Pr(\phi) = (1-\alpha)$, $Pr(g) = \alpha(1-\delta)$, and $Pr(b) = \alpha\delta$, respectively, where α is the probability that an information event occurs on a given day, and δ is the probability that the event is bad news. If a news event occurs, it is observed only by informed traders. If a good-news (bad-news) event occurs, the informed traders buy (sell) at the rate μ, and, whether or not a news event occurs, uninformed traders buy and sell at the rates ϵ_B and ϵ_S, respectively. Unlike most other studies, we estimate the five parameters ($\alpha, \delta, \mu, \epsilon_B$, and ϵ_S) on a quarterly basis, as in Brennan et al. (2016a), for the reasons described above.

Furthermore, following Brennan, Huh, and Subrahmanyam (2016b), we compute the daily posterior probability that a trading day was a no-news, good-news, or bad-news day, conditional on observing the numbers of daily buyer-initiated trades (B) and seller-initiated trades (S) on that day. The market maker in the model is assumed to update his assessment about the probabilities of the three types of events on a given day as he observes order flows. Using Bayes' rule, the posterior probability that no information event has occurred on a given day, conditional on observing B and S, can be expressed as:

$$Pr(\phi|B,S) = \frac{Pr(B,S|\phi)Pr(\phi)}{Pr(B,S|\phi)Pr(\phi) + Pr(B,S|g)Pr(g) + Pr(B,S|b)Pr(b)}. \tag{3}$$

Similar expressions can be derived for the other two probabilities: the posterior probabilities, conditional on observing B and S, that good news and bad news events have occurred on a given day. They are denoted by $Pr(g|B,S)$ and $Pr(b|B,S)$, respectively. Then, the three daily conditional probabilities are given by:

$$\pi(\phi|B,S) \equiv Pr(\phi|B,S) = \frac{(\alpha-1)e^{\mu}\epsilon_B^B\epsilon_S^S}{\alpha(\delta-1)\epsilon_S^S(\epsilon_B+\mu)^B - \epsilon_B^B[\alpha\delta(\epsilon_S+\mu)^S + (1-\alpha)e^{\mu}\epsilon_S^S]} \tag{4}$$

$$\pi(g|B,S) \equiv Pr(g|B,S) = \frac{\alpha(\delta-1)\epsilon_S^S(\epsilon_B+\mu)^B}{\alpha(\delta-1)\epsilon_S^S(\epsilon_B+\mu)^B - \epsilon_B^B[\alpha\delta(\epsilon_S+\mu)^S + (1-\alpha)e^{\mu}\epsilon_S^S]} \tag{5}$$

$$\pi(b|B,S) \equiv Pr(b|B,S) = \frac{\alpha\delta\epsilon_B^B(\epsilon_S+\mu)^S}{\epsilon_B^B[\alpha\delta(\epsilon_S+\mu)^S + (1-\alpha)e^{\mu}\epsilon_S^S] - \alpha(\delta-1)\epsilon_S^S(\epsilon_B+\mu)^S}. \tag{6}$$

To be brief, we denote these posterior probabilities calculated each day as π_ϕ, π_g, and π_b, respectively. Then, the posterior probability, conditional on observing B and S, that an information event has occurred on a given day is defined by $\pi_e = (1 - \pi_\phi)$. To be included in our sample, stocks must have at least 40 positive volume days within each quarter. Given the daily buys (B) and sells (S) processed via the Lee-Ready (1991) and Holden-Jacobsen (2014) algorithms, as well as the five parameters ($\alpha, \delta, \mu, \epsilon_B$, and ϵ_S) estimated each quarter based on the Yan and Zhang (2010) algorithm, we then compute the daily conditional probabilities (π_ϕ, π_g, and π_b) using Eqs. (4)-(6).

With the daily conditional measure of informed trading on good news (π_g) available, we can compute the quarterly average (π_g^Q) of monthly values in π_g^M, which is in turn the monthly average of daily values in π_g. Because the quarterly measure of informed trading will be used as the dependent variable in subsequent regression analyses and π_g^Q itself is bounded by [0, 1], we perform a logit-transformation of the raw measure (π_g^Q) to obtain our second measure of informed trading, Π_g, as follows:[6]

$$\Pi_g = \ln\left(\frac{\pi_g^Q}{1-\pi_g^Q}\right). \tag{7}$$

Given that obtaining patent approvals and receiving patent citations are mostly good-news corporate events, Π_g will be employed as the second measure of informed trading. Previous studies show that markets and investors under-react to good news (e.g., Frazzini, 2006; Tetlock, 2007). Thus, Π_g is an intuitive measure of informed trading in the context of corporate innovation. As a robustness check, however, we also use a more general measure: the conditional

[6] For the issue of logit-transforming dependent variables, see Morck, Yeung, and Yu (2000) and Karolyi, Lee, and van Dijk (2012), for instance.

probability of informed trading, $\Pi_e = \ln\left(\frac{\pi_e^Q}{1-\pi_e^Q}\right)$, where π_e^Q is defined similarly to π_g^Q.

2.2. Measures of Patent-Related News

To investigate how informed investors react to patent news, we construct the measures of patenting performance. We first collect the patent records of all U.S. public firms from the Harvard Business School patent inventor data of Lai et al. (2014) as well as from the updated NBER patent data.[7] The data sets contain all patents officially approved by the USPTO from 1976 to 2010.[8] From these two sources, we retrieve each patent's information about its application year-quarter, grant year-quarter, technology class, and Compustat-matched identifiers (GVKEY) of its assignee (i.e., the firm that files the patent application) for each patent granted during the 1990-2010 period. Since the USPTO announces the contents of granted (i.e., approved) patents in the weekly *Official Gazette*, each firm's granted patents in each quarter are thus public information to all investors. We thus choose the grant year-quarter as our time placer in examining the relation between patent news and informed trading. We then compute the following three variables to capture the intensity of patent news on a quarterly basis:

$NPAT$: The number of patents granted to a firm in each quarter.

$NCITE$: The number of citations received by patents granted to a firm in each quarter. For each patent, we count the number of citations received by the end of 2010 and then sum up the numbers of citations across all patents granted to a firm in each quarter.

VAL: The economic value (in \$1,000) of all patents granted to a firm in each quarter. This data set was used in Kogan, Papanikolaou, Seru, and Stoffman (2015), and we obtain it from Dimitris Papanikolaou's website.[9]

[7] The updated NBER patent data are available at: https://sites.google.com/site/patentdataproject/Home. We update patent data to 2010 following Chen, Chen, Hsu, and Podolski (2016).

[8] We use patent data instead of R&D expenses to proxy for corporate innovation for the following reasons. First, patent data contain richer information about the utility, procedure, and application of individual inventions. It is more difficult to interpret the implications of reported R&D expenses, which are the aggregated total of all R&D investments. Second, R&D investments are expensed and thus cannot be appropriately priced or transferred. Third, managers have an incentive to manipulate reported R&D expenses. Griliches (1990) thus states, "[n]othing else even comes close in the quantity of available data, accessibility, and the potential industrial, organizational, and technological detail." Lev (1999) also comments, "Research capability should be assessed primarily by output measures, such as the number of new products,... the number of patents, patent citations, and trademarks registered..." (p.32).

[9] To compute the economic value of a patent, Kogan et al. (2015) use the stock market reaction around its announcement date. Specifically, for a patent granted on a Tuesday of a week, they first calculate a firm's cumulative abnormal return (CAR) from that day to the Thursday of the same week (a three-day window). They then adjust this return for the fixed effects (for firm, year, day of the week, and estimation errors due

The first two variables defined above (*NPAT* and *NCITE*) are simple proxies for corporate innovation performance. While *NPAT* reflects each firm's innovation performance from a quantitative perspective (Scherer, 1965, 1967, and 1984), *NCITE* reflects each firm's innovation from a qualitative perspective, because the number of subsequent citations effectively captures the technical advancement of its invention (Trajtenberg, 1990; Harhoff et al., 1999; Hall, Jaffe, and Trajtenberg, 2005). However, these two measures are subject to heterogeneous technological characteristics. For example, some tech-intensive firms tend to generate more patents or receive more citations than others. For this study, therefore, we construct more appropriate proxies for corporate innovation or patent-related news that incorporate such heterogeneity across industries, by adjusting *NPAT* and *NCITE* as follows:

$ANPAT$: The natural logarithm of one plus the sum of adjusted patent counts (*adj-NPAT*) granted in each quarter, where *adj-NPAT* is computed in three steps [in the spirit of Bena and Li (2014)]. That is, (i) for each technology class in each quarter, the average number of patents granted to firms that are granted at least one patent in the class in the quarter is calculated; (ii) the focal firm's patent number in the class in the quarter is scaled by the average number calculated in step (i) to get the firm's adjusted patent counts in that class; and (iii) all the adjusted patent counts are added across all classes in the quarter to obtain *adj-NPAT* for the firm.

$ANCITE$: The natural logarithm of one plus the number of adjusted patent citations (*adj-NCITE*), which is computed in three steps. That is, (i) for each technology class in each quarter, the average number of subsequent citations received (up to 2010) by the patents granted to the firms in this class is calculated; (ii) the number of subsequent citations received by the patent granted to the firm in the class in the quarter is scaled by the average number of citations calculated in step (i) to obtain the firm's adjusted patent citations in the class; and (iii) all the adjusted patent citations are added across all classes in the quarter to obtain *adj-NCITE* for the firm. Thus, this variable effectively reflects the quality of the patents granted to a firm.

Since the third measure (*VAL*) is estimated based on how the news about patents granted to a firm is reflected in its stock price around the announcement date, *VAL* is an 'indirect'

to high volatility during the three-day period). Lastly, they multiply the adjusted return by the firm's stock market capitalization on the day before the announcement date, obtaining the economic value of a patent. If there are more than one patent granted to a firm on the same day, the firm value change is equally divided by the number of patents and assigned to each patent. Thus, *VAL* is the total value changes aggregated across all patents granted to the firm in a given quarter. To consider price changes over time, *VAL* is adjusted for inflation.

measure of patenting activities. Since we assume that the industry heterogeneity in *VAL* is already adjusted by the stock market, we simply use the log-transform of *VAL* as follows:

$AVAL$: The natural logarithm of one plus quarterly VAL.

2.3. Data, Control Variables, and Descriptive Statistics

To construct Ω and Π_g using ISSM/TAQ for NYSE/AMEX-listed firms, we find that the total number of trades classified as buys or sells (by matching them to bid/ask quotes) is 21.59 billion (excluding trades executed at the quote mid-points) over the 21-year period from January 1990 to December 2010. On average there were 85.69 million trades each month, and the highest number of trades in a given month was 800.13 million in October 2008. For each firm there were on average 26,138.3 trades in a month, excluding trades executed at the quote mid-points, but some firms experienced much more intensive trading in recent months: the number of trades in Bank of America was 14,046,042 in April 2009.[10]

Table 1 reports descriptive statistics for the key variables. The cross-sectional value for each of the five statistics is first calculated each quarter and then the time-series average of those statistics is reported. The sample period is the past 84 quarters (1990:Q1-2010:Q4) for NYSE/AMEX-listed firms. We use ordinary common stocks only (SHRCD = 10 or 11 in CRSP). The availability of *dIH* (defined below) limits our analyses to the period of 1990-2010. The sample includes only the firms that have positive values in *NPAT* in a quarter. Thus, the average number of firms used each quarter is relatively small (269.2), compared to the average number that also includes firms with no patent (about 1,750.6: see Table 2 and Subsection 3.3.3.). The total number of firm-quarter observations over the 84 quarters is 22,613.

Table 1 shows that the informed trading measure constructed based on both price impact and order imbalance (Ω) is 0.096 on average over the 84 quarters. The conditional probability of informed trading on good news (π_g^Q) is 0.282, and its logit-transform (Π_g) is -1.482 on average. The logit-transformation makes the measure more skewed and leptokurtic. The middle part of the table reports the statistics for the innovation-related variables. A typical firm obtains 14.8 patents (*NPAT*) per quarter on average and receives 207.2 patent citations (*NCITE*). When the numbers of patents and citations are adjusted for heterogeneity as discussed earlier (and

[10]The Holden-Jacobsen (2014) algorithm uses all trades across different exchanges to find NBBO quotes and matches them with trades. Therefore, the number of trades used in this algorithm is much larger than the number of trades used in the Lee-Ready (1991) method.

log-transformed), the mean value of the adjusted patent counts ($ANPAT$) is 1.030 per quarter while that of the adjusted citations ($ANCITE$) is 2.705. Given that the two adjusted variables are log-transformed, we find that they become much less skewed and leptokurtic. The indirect measure of patenting activities (VAL) shows that the market value of a firm increases by about $279.2 million around the announcement date owing to the patent(s) newly granted to the firm in a given quarter. Its log-transform ($AVAL$) is less skewed and leptokurtic than VAL.

Other control variables to be used in our regression analyses are defined as follows:

R&D: The ratio (in %) of quarterly research and development expenses (in $million) to quarter-end assets (in $million), and 0 if the expenses are missing. We include this as a control variable because the R&D expenses are commonly used as a proxy for corporate innovation investments, and usually lead to information asymmetry associated with innovation activities (Aboody and Lev, 2000; Aslan et al., 2011; Seru, 2014).

dIH: The quarterly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding. Insider holdings are taken from the Insider Filing Table 1 (Stock Transactions) in the Thomson Reuters database, and the value for any given month is the latest value reported in the database. The data are available from 1986 but are sparse before 1990, so using this variable limits our analyses to a sample period starting from 1990. We use the change in insider holdings (dIH) because it is more relevant to insider-trading activities than IH itself.

ROA: The the ratio (in %) of quarterly net income (in $million) to quarter-end assets (in $million), and 0 if missing. It is obtained from Compustat (Fundamentals Quarterly).

$RVOLA$: The quarterly average of monthly values in σ (in %), which is the standard deviation of daily returns within a month. This measure of return volatility (computed from CRSP) is used as a proxy for the arrival rate of information.

BTM: The ratio of quarter-end book value (in $million) to quarter-end market capitalization (in $million). We include it in regression analyses due to the possibility that glamour stocks with low BTM may have more cash-flow uncertainty and more room for informed trading.

$NANA$: The number of analysts following a firm. We use this variable because analyst coverage may increase or decrease informed trading. Some studies argue that broader analyst coverage reduces information asymmetry. However, a recent $50 million fine imposed on Citigroup

Global Markets Inc. provides strong evidence that research activities by analysts may increase information asymmetry and hence informed trading in a firm, because analysts selectively disseminate research results to their clients.[11]

LDV: The one-quarter lag of the dependent variable (Ω or Π_g). We include *LDV* in pooled regressions to control for persistence in Ω and Π_g.

The lower part of Table 1 shows that quarterly R&D expenses relative to assets (*R&D*) is on average 1.06% in a sample firm. The average book-to-market ratio (*BTM*) is 0.51. The mean value of *dIH* (-0.1%) implies that insiders are more likely to sell than to buy in general. The quarterly average of monthly return volatility (*RVOLA*) is 2.35%. The number of analysts that follow a firm (*NANA*) is 10.0 on average.

The extent of information asymmetry and informed trading may differ across industries due to unobservable industry characteristics. To control for the industry fixed effects in our analyses, industry dummy variables are also constructed based on the Fama-French 12-industry classification method (the vector of 12 dummies is denoted by *IDUM*). The 12 industries and associated dummy variables (*IDUM01-IDUM12*) are described in Table 2. *IDUM12* is the base case and thus it will be excluded in cross-sectional and pooled regressions.

Table 2 reports basic statistics of the innovation-related variables by industry. We see that out of the total 1,750.6 firms (including firms with no patent), about 262.3 firms (15.0%) obtain at least one patent each quarter. The manufacturing (*Manuf*) and business equipment (*BusEq*) industries have the largest number of firms (on average 81.4 and 54.3 firms, respectively) that

[11] There is ample evidence that analysts disseminate research results selectively to their clients. A November 24, 2014 article by Reuters (Fortune Magazine) reports, "The supervision lapses at Citigroup Global Markets Inc., which occurred between January 2005 and February 2014,... One example of Citigroup's conduct involved dinners that equity research analysts hosted...the analysts discussed stock picks that in some cases were not consistent with the research they published....In another instance, an analyst at a Taiwan-based Citigroup affiliate 'selectively disseminated' research about Apple Inc...which a Citigroup equity sales employee then related, selectively, to other clients, FINRA said..." A related article by Matt Levine at Bloomberg describes, "... CGMI equity research analysts engaged in frequent communications... These frequent interactions took place by email, over the phone and in-person, and at meetings, social events and other functions hosted or attended by CGMI equity research analysts... Citi wants to please those clients, and providing them with differentiated access to analysts apparently pleases them..." Another article reported on December 11, 2014 by Eric Garcia at Marketwatch.com states, "Ten firms have been fined $43.5 million for allowing equity research analysts to solicit investment banking business and giving favorable research to Toys "R" US' initial public offering. Among the companies the Financial Industry Regulatory Authority fined were Barclays, Goldman Sachs, Credit Suisse, JP Morgan Securities, Deutsche Bank Securities, Merril Lynch unit of Bank of America, Morgan Stanley, Wells Fargo,... FINRA found that Toys "R" Us and its private equity owners invited the firms..., asking equity research analysts to make presentations ensuring their views were aligned with investment bankers, with each of them offering favorable research in return for a role in the IPO..."

acquire non-zero patents in each quarter. In relative terms, however, the chemical industry (*Chems*) has the highest proportion (39.7%) of firms with non-zero patents: out of the 63.9 companies in the industry, 25.3 companies obtain at least one patent each quarter. The consumer durables (*Durbl*), business equipment (*BusEq*), and manufacturing (*Manuf*) industries also have large proportions of such firms. The utilities (*Utils*) and finance (*Money*) industries have the smallest number of firms that obtain patents in both absolute and relative terms.

A more interesting question is, in which industries do firms acquire more patents, receive more citations, and experience larger increases in their market value owing to the granted patents? The last three columns in Table 2 show that firms in the telecom industry (*Telcm*) get the largest number (53.1) on average. Moreover, firms in this industry receive the most frequent patent citations (1,257.2) and have the largest market-value increase ($1.61 billion). Firms in the business equipment industry (*BusEq*) have the second largest numbers of patents (26.7) and citations (460.0), but the healthcare (*Hlth*) firms experience the second largest increase in the their market value. The healthcare (*Hlth*) and consumer durables (*Durbl*) industries also have relatively large numbers of both patents and citations.

3. Patent-Related News and Informed Trading

3.1. Univariate Analyses with Portfolios

As a preliminary test to examine if news about corporate innovation has any relation to informed trading, we form portfolios by sorting on each of the three patent-news measures. That is, in each quarter we sort component firms (that have positive values in the patent-news measures) on one of the three patent-news measures as of the previous quarter (i.e., $ANPAT_{t-1}$, $ANCITE_{t-1}$, or $AVAL_{t-1}$) to split them into five portfolios. We next calculate the cross-sectional mean of the informed trading measure as of the current quarter (i.e., Ω_t and $\Pi_{g,t}$) for each portfolio. Then the time-series average of the cross-sectional means over the sample period is reported for each portfolio. We also report the average number of component stocks used in each portfolio in each quarter. In the portfolio analyses, we report the average of the raw measure (π_g^Q), instead of the logit-transformed one (Π_g), for interpretational convenience.

Table 3 shows that the average number of component stocks (*Avg Obs*) used in each portfolio in each quarter ranges from 47.6 to 51.5. When the portfolios are formed by sorting on *ANPAT* in Panel A, both measures of informed trading (Ω and π_g^Q) are monotonically increasing in the patent-related measure (*ANPAT*). In addition, the null hypothesis that informed trading in the ($High - Low$) portfolio is zero is resoundingly rejected. When the portfolios are sorted on *ANCITE* or *AVAL* (Panel B or C), the results are similar. In sum, the portfolio analyses in Table 3 provide preliminary evidence that patent news causes or predicts informed trading.

3.2. Multivariate Analyses: Regressions with Individual Firms

3.2.1. Cross-sectional Regressions

We begin by Fama and MacBeth (1973) cross-sectional regressions using the firms that have positive values in *NPAT*. At the time a patent is granted to a firm and this news is announced, we expect that sophisticated investors react to this news contemporaneously or with some time lags [since investors may under-react to public news (e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998; Frazzini, 2006; Tetlock, 2007)].[12] Given the possible under-reaction, we allow the dependent variable to be contemporaneous, one quarter led, or two quarters led. That is, each quarter we run the cross-sectional regression:

$$IT_{it+l} = a + \phi_i \Lambda_{it} + \sum_{j=1}^{J} b_{ji} X_{jit} + \epsilon_{it+l}, \tag{8}$$

where IT_{it} is one of the two informed trading measures (Ω or Π_g) for firm i in quarter t; Λ_{it} is one of the three patent-news measures (*ANPAT*, *ANCITE*, or *AVAL*); and X_{jit} includes the control variables defined above (*R&D, dIH, ROA, RVOLA, BTM, NANA*, and *IDUM*). *IDUM* stands for the 11 industry dummies (*IDUM01-IDUM11*: *IDUM12* is excluded) described in Table 2. The subscript l is the number of quarters by which the dependent variable is led.

As mentioned above, considering the possibility that informed trading may occur after the grant quarter (or under-react), we examine the effects of corporate innovation and other control variables contemporaneously as well as with leads up to two quarters: i.e., $l = 0, 1$, or 2 in Eq. (8).[13] Following Fama and MacBeth (1973), we obtain the final estimator that is the time-series

[12] The Daniel, Hirshleifer, and Subrahmanyam (1998) model predicts that investors under-react to public information and over-react to private information. Frazzini (2006) and Tetlock (2007) also show that investors under-react to good-news information.

[13] Since most of the control variables are available on a quarterly basis, we estimate Eq. (8) quarterly. To emphasize the predictability (because of under-reaction to patenting outcomes) of informed trading by patenting

average of the quarterly coefficients. Since the dependent variable (Ω or Π_g) is persistent, we report heteroskedasticity- and autocorrelation-consistent (HAC) t-statistics computed based on Newey and West (1987).[14]

Table 4 reports the estimation results with Λ_i in Eq.(8) being the number of granted patents ($ANPAT$): the dependent variable is the informed trading measure constructed based on both price impact and order imbalance (Ω) in Panel A, and the conditional probability of informed trading on good news (Π_g) in Panel B. The regression coefficients in Table 4 (and all subsequent tables) are multiplied by 10 for expositional convenience. The average number of component firms (*Avg Obs*) used each quarter over the 21-year (84-quarter) period is 256.5-261.4 in Panel A, depending on the availability of data. The average of adjusted R-squared from individual regressions (*Avg Adj-Rsqr*) in Panel A ranges from 15.1% to 16.8%.

Specification (i) in Panel A shows that patent news proxied by $ANPAT$ is strongly positively associated with informed trading (Ω) contemporaneously. This means that informed traders buy on the news about innovation performance. This confirms our finding in the portfolio analyses above: indeed patent-related news induces informed trading. To get a feel for the impact of patent news on informed trading, we find in specification (i) that a one-standard-deviation increase in $ANPAT$ (0.822) is associated with an increase in Ω of 0.041, which is equivalent to a 42.7% increase relative to the sample average (0.096) of Ω and an increase that constitutes 15.8% of its standard deviation (0.260).

Looking at the effects of other variables in specification (i) in Panel A, the more profitable (measured by ROA) a firm is, the more informed trading it is subject to. As expected, glamour stocks with low book-to-market ratios (BTM) seem to have more cash-flow uncertainty and thus more room for informed trading. Higher return volatility ($RVOLA$) is also related to more informed trading. We find that research activities by analysts ($NANA$) increase informed trading for the reason described in footnote 11. Note here that our sample includes innovative firms only. So their innovativeness would attract broader analyst following. In addition, the complexity of involved technologies in such firms leads to higher profitability to informed traders,

activities, we use the lead order ($t+l$, where $l=0,1,2$) in the dependent variable in Eq. (8), rather than using the lag order ($t-l$, where $l=0,1,2$) in the explanatory variables. We examine the lead-lag relations up to two quarters as the literature has often shown that informed investors trade on information up to two quarters from the event time (see e.g., Ali, Durtschi, Lev, and Trobley, 2004).

[14] As suggested by Newey and West (1987) in choosing bandwidth parameter $N(=L+1)$ for the Bartlett kernel to compute the standard errors, we let the lag length L be equal to the integer portion of $4(T/100)^{2/9}$, where T is the number of observations in the estimated coefficient series.

if they have information advantage or are skillful in interpreting the value of related patents.

Next, we examine whether *ANPAT* can predict informed trading or, differently put, whether informed trading occurs later after the patent is finally granted to a firm. With lead orders $l = 1$ and 2 in Panel A, the coefficients on *ANPAT* are significant at 1% all across different specifications, although its impact (the magnitude of the coefficients) becomes smaller. We find in specification (ii) that the impact of innovation performance (*ANPAT*) in the current period on informed trading (Ω) in the following quarter is slightly lower than that in specification (i). We again observe a smaller impact in specification (iii) that predicts informed trading two quarters ahead, but it is still economically significant. These results strongly suggest that corporate innovation activities lead to information asymmetry and hence informed trading (buying) not only contemporaneously but also with some time lags. Discernible is that while the predictability of *ROA, RVOLA*, *BTM*, and *NANA* remains significant, *R&D* plays no role after controlling for *ANPAT*.

The dependent variable, Ω, used in Panel A is an intuitive measure of informed trading. But the sign of the measure on a given trading day is determined by the daily aggregated order imbalance, dictating that trades are based on either good-news information alone ($\Omega > 0$) or bad-news information alone ($\Omega < 0$) on that day. On a given trading day, however, both good news and bad news can arrive in securities markets at the same time or with time differences. Thus, it is reasonable to assume that some informed trades are made based on good news and others are based on bad news on each trading day. Eqs.(5) and (6) allow us to compute each day the probability of informed trading on good news and the probability on bad news separately. Since it is good news for an innovative firm to obtain patents and for granted patents to receive citations, it is sensible to use the conditional probability of informed trading on good news, Π_g, as the dependent variable. The results are reported in Panel B of Table 4.

As Panel B shows, *ANPAT* is strongly positively associated with the probability of informed trading on good news. To gauge the impact of the innovation activities on informed trading, a one-standard-deviation increase in *ANPAT* in the current quarter leads to an increase in Π_g of 0.158 in the current quarter [see specification (iv)], which is equivalent to a 10.7% increase (in absolute terms) relative to the sample average (-1.482) of Π_g and an increase that accounts for 5.8% of its standard deviation (2.735). The reduced levels of economic significance seem natural, because Π_g is designed to capture only one-side of trading. Nonetheless, the above results lend strong support to our conjecture that informed or skilled investors buy on good-news information contemporaneously as well as with time lags, although the degree of informed trading becomes weaker over time. Other noteworthy aspects with Π_g are that the effects of *ROA* and *BTM* disappear with $l = 1$ and 2, and *RVOLA* tends to be negatively related to informed trading in the future periods.

How many patents a firm obtains is a reasonable measure of its added intellectual property, but the number *per se* may not represent the influence of the patents. Another relevant aspect is how many citations the patents receive from other patents. Therefore, we examine the relation between the quality of innovating activities and informed trading using the number of patent citations (*ANCITE*) in Table 5. In terms of the relations of informed trading to *ANCITE* and other explanatory variables, the results are very similar to those observed in Table 4. As we see in Panel A of Table 5, the loadings on *ANCITE* are all positive and statistically significant at any conventional level, demonstrating that patent citations also cause informed buying, which is measured by Ω. When we let the dependent variable (Π_g) capture only the informed trading on good news in Panel B, the economic significance decreases as before. The impact of *ANCITE* also becomes weaker over time (i.e., with $l = 1$ or 2). However, the results in Panel B imply that the citation effect on Π_g is never trivial.

Next, we examine the relation using *AVAL*, which is an indirect measure of patent news in the sense that the quality of patenting activities are computed based on the responses of market participants to the news on granted patents. Thus, *AVAL* reflects how investors assess the value of patents in the stock market. Panel A in Table 6 shows that *AVAL* is an important determinant or predictor of Ω. For instance, specification (ii) in Panel A shows that a one-standard-deviation increase in *AVAL* (2.229) in the current quarter leads to an increase in Ω of 0.054 in the following quarter, which is equivalent to a 56.3% increase relative to the sample average (0.096) of Ω and an increase constituting 20.8% of its standard deviation (0.260). *ROA* and *RVOLA* have positive effects on informed trading, while the effects of *BTM* and *NANA* tend to turn marginal. We find in Panel B that the impact of *AVAL* on Π_g is also statistically strong, confirming that the economic value of patents induces informed trading contemporaneously and with time lags. With Π_g as the dependent variable, *ROA* and *RVOLA* are positively associated with informed trading only in the contemporaneous regression.

3.2.2. Pooled Regressions to Control for Time-Varying Effects

The cross-sectional regressions in Tables 4-6 provide a remarkable snapshot about how patent news is related to information asymmetry and informed trading. However, Fama-MacBeth regressions may not control for other potentially important effects that are time-varying. Thus, in this subsection, we conduct pooled regressions to control for the lagged dependent variable (LDV) and to control for any industry or year fixed effects. By including LDV in the pooled regressions, we can control for the persistence of the dependent variable. We do not include firm fixed effects in pooled regressions, considering that, as a firm's innovation performance is highly correlated with its individual effect, a large portion of the effect of patent news on informed trading will be absorbed by firm fixed effects (Blundell, Griffiths, and Van Reenen, 1999; Hall, Jaffe, and Trajtenberg, 2005; Hall, Thoma, and Torrisi, 2007; Noel and Schankerman, 2013).

Table 7 contains the results from pooled regressions equivalent to Eq. (8). Panels A-C control for the year fixed effects (1990-2010: 2010 is the base case), as well as the industry effects. To control for persistence in the dependent variable, we also include in each panel the dependent variable lagged by one quarter (LDV). The three panels show that the total number of firm-quarters (Obs) used in the pooled regressions ranges from 19,360 to 22,573. The adjusted R-squared (*Adj-Rsqr*) is generally lower again in the regressions for Π_g than those for Ω.

We find in Panel A that, whether the dependent variable is Ω or Π_g, patent news proxied by the number of patents, $ANPAT$, exerts a significant impact on informed trading in the current period and up to two quarters ahead, even after accounting for other effects considered important in the literature. With Ω as the dependent variable in specifications (i)-(iii), a one-standard-deviation increase in $ANPAT$ in the current quarter induces substantially higher informed trading in the current quarter or future periods: a 47.9%-50.0% increase in Ω relative to its sample average. With our second measure as the dependent variable in specifications (iv)-(vi), while the t-values for the coefficients on $ANPAT$ tend to be greater, the impact of it on informed trading is again smaller: a similar amount of increase in $ANPAT$ in the current quarter causes informed trading proxied by Π_g to increase by 8.0%-9.9% relative to its sample average, contemporaneously or with time lags. The impact of patent news on informed trading is again largest in the contemporaneous specifications [(i) and (iv)].

The coefficient on $NANA$ is positive and significant across all specifications in Panel A, suggesting that firms with broader analyst coverage are subject to more informed trading. Firms with higher profitability (*ROA*) appear to have more room for informed trading. *R&D* does not play a significant role in most cases after controlling for *ANPAT*. The effects of *dIH* and *RVOLA* are not consistent across specifications with Ω vs. Π_g. Glamour stocks with low book-to-market ratios seem to be more vulnerable to cash-flow uncertainty and hence more informed trading, as *BTM* tends to be negatively associated with the informed trading measures (especially with Ω). The coefficient on *LDV* is all positive but significant only when the dependent variable is Π_g with the lead order $l = 1$ and 2.

When the number of patent citations, *ANCITE*, is employed as a proxy for patent news in Panel B, the results are quite similar. To be brief, *ANCITE* is strongly positively associated with the two measures of informed trading (Ω and Π_g). As to its economic significance, a one-standard-deviation increase in *ANCITE* in the current quarter induces more informed trading contemporaneously or later by the amounts similar to those estimated above for the impact of *ANPAT* in Panel A. Rather than repeating on the effects of other control variables, we briefly discuss the industry effects here. As we have seen Table 2, the telecom industry (*IDUM07*) is characterized by the lion's share of granted patents and citations. Our (untabulated) results show that indeed this industry is highly subject to informed trading. Firms in the business equipment industry (*IDUM06*) obtain relatively large numbers of patents and citations, and so the industry has more room for informed trading. On the other hand, consumer non-durables, durables, and wholesale/retail industries (*IDUM01, IDUM02*, and *IDUM09*, respectively) are less vulnerable to informed trading, compared to the 'Other' industry (*IDUM12*).

When the patent news is proxied by *AVAL* in Panel C, we find that the results are comparable to those in the previous two panels. Whether the dependent variable is Ω or Π_g, *AVAL* has a significant impact on informed trading in the current period, as well as up to two quarters ahead (but to a lesser degree with $l = 1$ or 2). In Panel C, the effects of the control variables become insignificant or much weaker, similarly to the results shown in Table 6.

3.3. Robustness Tests

In this subsection, we conduct additional tests to examine the robustness of our baseline results. We have so far used three measures to proxy for patent-related news. However, there are some issues in using *ANCITE* and *AVAL*. To construct *ANCITE*, for a given quarter we count the number of citations that each patent will receive from that quarter to the end of 2010.

This induces a look-ahead bias in the analyses, because the number is not known as of that quarter. Also, *AVAL* is constructed based on the 3-day response of the stock price to patent approvals, CAR(0, +2). However, trading on (private) information could occur well before the announcement (i.e., insider trading, which is beyond the scope of our study). In addition, trading on (public) information does occur gradually over time after the announcement, as we have discussed above. Patent news is thus impounded in stock prices over a longer (than a 3-day) period of time before and after the patent approval/announcement. This suggests that *AVAL* may not fully capture the economic value of patenting activities. Given these aspects of the two innovation measures as well as for brevity, we will report only the results from using *ANPAT* in most of the remaining analyses.[15]

3.3.1. With Ω_m as a Measure of Informed Trading

Our first measure of informed trading (Ω) used so far is the average of the daily measures (ω^D's), for which current month's daily order imbalances ($DOIMB^D$'s) are multiplied by previous month's price impact (λ^{FV}_{m-1}) to get around a look-ahead bias. Our question is whether the results will change if the informed trading measure is computed in a different way.

To investigate this possibility, we obtain the measure as follows. Given the daily aggregated buy and sell volume ($B and $S) in $million, the monthly dollar-volume order imbalance ($DOIMB^m$) is calculated as the monthly aggregated (over trading days within each month) buyer-initiated dollar volume ($\$B^m$) minus the monthly aggregated seller-initiated dollar volume ($\$S^m$): i.e., $DOIMB^m = (\$B^m - \$S^m)$. Then the monthly measure is given by $\omega^m = \lambda^{FV,m} * DOIMB^m$, where $\lambda^{FV,m}$ is the monthly price-impact parameter estimated using intradaily dollar order flows within the current month.[16] The quarterly measure, Ω_m, is now obtained as the average of monthly ω^m's within each quarter.

The results with the new measure (Ω_m) are reported in Panel A of Table 8. To compare the results with those reported in Panel A of Table 7, the statistical significance of *ANPAT* is similar to that of the corresponding specifications [(i)-(iii) in Panel A of Table 7]. We also find that the economic significance of a one-standard-deviation increase in *ANPAT* is associated with informed trading (Ω_m) higher by the amount equivalent to or slightly larger than the case

[15] The (unreported) analyses that use *ANCITE* and *AVAL* are qualitatively similar to those with *ANPAT*.

[16] In this case, a look-ahead bias is not an issue. In computing ω^m, therefore, we use the current month's price impact, $\lambda^{FV,m}$.

with Ω reported in Table 7. The effects of other control variables are qualitatively similar.

3.3.2. With Π_e as a Measure of Informed Trading

Considering that obtaining patent approvals are good-news events in a firm, we have used the conditional probability of informed trading on good news (Π_g) as one of the two measures in Tables 1-7. By construction, Π_g is designed to capture only one side of informed trading. However, there might be both good and bad news involved in patenting activities. In this subsection, we conduct a robustness test using a measure that captures both sides of informed trading: i.e., Π_e. To obtain this measure, we first compute the daily conditional probabilities π_ϕ and π_e [$= (1 - \pi_\phi)$] using Eq. (4). Then π_e^M is calculated as the monthly average of daily π_e's, and π_e^Q as the quarterly average of monthly π_e^M's within each quarter. Since π_e^Q is bounded by [0, 1], it is logit-transformed to obtain Π_e [$= \ln\left(\frac{\pi_e^Q}{1-\pi_e^Q}\right)$] as the dependent variable.

Panel B in Table 8 shows that *Adj-Rsqr* more than doubles when Π_e is used, compared to the corresponding results with Π_g [see specifications (iv)-(vi) in Panel A of Table 7]. The statistical significance of the loadings on $ANPAT$ and their impact on informed trading tend to strengthen as well: a one-standard-deviation increase in $ANPAT$ induces informed trading to increase by about 33%-40% relative to the sample average of Π_e.

Innovative firms file applications for patents with the USPTO, and all or some of the patents are granted eventually. Unfortunately, information regarding unsuccessful applications is not provided by the USPTO. This means that announcements of patent approvals and patent citations are more likely to be positive news than negative news to the inventor firms. Therefore, we continue to use Π_g in subsequent analyses.

3.3.3. Including Firms with a Value of Zero in the Number of Patents or Citations

More than half of NYSE/AMEX-listed firms do not actively acquire or hold any patent. One natural question is how our empirical results would appear if firms with no patent (missing in the number of patents or citations) are included in the sample. To examine this issue, we replace the missing values in the two patent-news measures with zeroes and include those firms in the analyses. In that case, the average number of firms used each quarter for cross-sectional regressions increases substantially to 1,750.6 (from 269.2 shown in Table 1) and the total number of firm-quarters for pooled regressions is larger than 120,000 (vs. 22,613 in Table 1).

To save space, we do not report the results. However, we find that the innovation variables are even more strongly associated with informed trading, with the t-values for the coefficients being often two-digit numbers. The effects of other control variables are also qualitatively similar. Given the fact that a large proportion of NYSE/AMEX firms do not have any patent each quarter, we exclude such firms in our analyses.

4. Further Identification Tests

Our baseline results could be subject to endogeneity issues related to reverse causality or omitted variables. Reverse causality occurs when the dependent variable is persistent and affects an explanatory variable(s). However, there is no reason to believe that causality flows in the opposite direction in our case: it is unconvincing to believe that informed trading in a firm causes the news on granted patents contemporaneously. We have also presented a lead-lag relation between patent news and informed trading up to two quarters, and it is not likely that informed trading in a future period affects patent news in the current period. Even if both informed trading in a future period and patent news in the current period are determined by informed trading in the current period, patent news in the current period should not have any explanatory power for informed trading in a future period, given the presence of informed trading in the current period as observed in our regression results in Table 7. But our empirical results show that patent news still predicts informed trading even after controlling for informed trading in the current period. Thus, our findings are not subject to reverse causality.

There may be industry- or firm-level omitted variables that influence both informed trading and patent news, thereby leading to a positive relation between the two variables. In an unreported table, we control for all industry-level factors by including industry-year joint fixed effects, and we still have consistent results. We thus believe that our findings cannot be attributed to industry-specific omitted variables. However, although we include many plausible determinants of informed trading, we cannot rule out the possibility of firm-level omitted variables that would result in the positive relation between informed trading and patent news. In this section, therefore, we address the potential issue of firm-level omitted variables by conducting difference-in-differences regressions and two-stage least squares (2SLS) regressions.

4.1. Difference-in-Differences Regressions

We adopt a difference-in-differences (DiD) approach to exploit the exogenous 1998 policy shock to further identify the causality between patent news and informed trading. The court decision on the "State Street vs. Signature Financial Group" case in 1998 was an event unexpected by the general public. Since the court ruling, the intellectual property rights of firms in the finance and software industries were significantly strengthened after the decision (Hall, 2009).[17]

For a DiD test, we augment Eq. (8) with the following variables: an indicator variable, $I_{affected}$, which equals one if a firm is in the business equipment (including software) industry (*BusEq* in Table 2) or the finance industry (*Money*), and zero otherwise; an indicator variable, I_{Y99on}, which equals one if the year is 1999 or after, and zero otherwise; a variable two-way interacted between the patent-news measure ($ANPAT$) and $I_{affected}$; a variable two-way interacted between $ANPAT$ and I_{Y99on}; and a variable three-way interacted among $ANPAT$, I_{Y99on}, and $I_{affected}$.

We are mainly interested in the behavior of the three-way interacted variable ($ANPAT$* I_{Y99on}*$I_{affected}$), because it captures the effect of patent news on informed trading, conditional on the exogenous shock to firms belong to specific industries. The idea is that if patent news induces informed trading, then such a relation should be strengthened in the affected firms since 1999, because patents of firms in those industries have become more valuable owing to the strengthened intellectual property rights. In using this exogenous shock, we limit our sample period to 16 quarters around the event (1997-2000), in order to meet both relevance and exclusion conditions. By narrowing down the sample period this way, we can pinpoint the effect of the court decision about the "State Street vs. Signature Financial Group" case on informed trading based on patenting activities, precluding any confounding effects caused by other economic factors or conditions that may also affect informed trading (except through innovation). In addition, it ensures that the impact of the decision varies across industries

[17] State Street Bank & Trust Company did businesses related to a patent titled "Data Processing System for Hub and Spoke Financial Services Configuration" (U.S. Patent No. 5193056) owned by Signature Financial Group, Inc. (SFG) since March 1993. Initially, State Street tried to license that patent from SFG but the negotiation failed. Instead of gaining a license for the patent usage, State Street then sued SFG in the Federal District Court in order to invalidate the patent by arguing that the patent is based on "pure numbers." The District Court agreed and invalidated the patent. However, SFG appealed the decision to the Federal Circuit Court and successfully reversed the District Court's decision in July 1998. The unanticipated success of SFG in defending its business method patent encouraged others who held patents on intangible business methods and algorithms to take more aggressive approaches in order to protect their intellectual properties.

and causes sufficient cross-sectional and time-series variations that do not coincide with other economic events or conditions.

Table 9 presents the test results from the pooled regressions that include all interacted terms discussed above as well as industry-year joint fixed effects. The table shows that the number of firm-quarters used for this experiment ranges from 4,914 to 5,044. In Panel A, we find that the effect of $ANPAT{*}I_{Y99on}{*}I_{affected}$ on Ω is not only positive but also strong in all three specifications. It is also noteworthy that the magnitude of the coefficient on the three-way interacted term is more than double the coefficient on $ANPAT$ itself. This indicates that the impact of the court decision on the patenting activities of the firms in the finance and business equipment industries is substantial, which in turn leads to more intensive informed trading in the firms belonging to the affected industries. When we use Π_g in Panel B, the statistical significance becomes generally weaker, but the effect is still strong for $l = 0$ and 1.

4.2. 2SLS Regressions with Instrumental Variables

We next conduct 2SLS regressions using two instrumental variables (IVs): (i) the average time taken from patent application to its grant (*AGTime*); and (ii) the number of patents granted three years ago (*NPATym3*). For each patent, we first calculate the application-grant time difference. Next, for each firm in each quarter, we compute the mean of the application-grant time differences across all patents owned by the firm and then obtain the time-series average of the cross-sectional means over the most recent 20 quarters, which results in *AGTime*.[18] Given that it takes on average two to three years for a patent application to be approved, this variable is lagged by 12 quarters (three years) to satisfy the exclusion condition. This variable reflects time costs of a firm's patenting activities and thus it is negatively related to the patent-news measure ($ANPAT$). The number of granted patents lagged by 12 quarters (*NPATym3*) reflects a firms' past innovation performance, which is positively correlated with its patent-news measure in the current period, given that innovative firms tend to keep producing patents. The two IVs satisfy the exclusion condition, since they are lagged by 12 quarters and thus not likely to affect informed trading except through firm-level granted patents in the current period. We formally

[18]Hsu et al. (2015) use the application-approval lag and the average R&D costs per patent as two IVs to mitigate the endogeneity concern. In this study, we do not consider R&D costs per patent as another instrumental variable, because of evidence that R&D costs are correlated with information asymmetry (e.g., Aboody and Lev, 2000; Aslan et al., 2011; Seru, 2014).

conduct statistical tests to verify if the above two variables are appropriate as instruments.

The results from 2SLS regressions are reported in Table 10. In the first stage, we regress the patent-news measure (*ANPAT*) on the two IVs (*AGTime* and *NPATym3*) as well as the control variables used in Eq. (8) to get the fitted (predicted) values of the patent-news measure. The fitted variable is denoted by *Fitted_ ANPAT*. Note that the fitted variable is purged of all firm-level omitted variables because they are estimated from the first-stage regression that contains only observable variables, including instrumental variables, control variables, and fixed effects. In the second stage, we regress the informed trading variable (Ω or Π_g) on the fitted patent-news measure (*Fitted_ ANPAT*) and other control variables. Therefore, the coefficients on the fitted measures in the second-stage regressions now represent the impact of patent news on informed trading free of firm-level omitted variables.

As we see in the two panels of Table 10, the coefficients on *Fitted_ ANPAT* are positive and significant. This finding indicates that the positive relation between patent news and informed trading is not driven by firm-level omitted variables. In the lower part of each panel, we report the *rk* LM-statistic (*Kleibergen-Paap Stat*) from the Kleibergen-Paap (2006) under-identification test for the relevance of the IVs, as well as the J-statistic (*Hansen J Stat*) from the Hansen (1982) over-identification test for their exclusiveness. The *p*-values confirm the validity of the instrumental variables: first, the under-identification test always rejects the null hypothesis of "no relevance," meaning that the proposed IVs can explain our patent-news measure; and second, the null hypothesis of "exclusiveness or exogeneity" is not rejected at the 5% level in any case, meaning that the proposed IVs are uncorrelated with the estimation errors from the original Eq. (8). To sum up, our results in Tables 9 and 10 collectively suggest that firm-level patent news causes informed trading, ruling out the influence of omitted variables.

5. Who is Active in Trading on Patent-Related News?

Given the technical complexity of granted patents, not all investors are suited for processing the related data and interpreting the implications of patent-related news. A natural question is then, specifically who is more active in trading on the news about corporate innovation? Our experiments in this section are based on the assumption that institutional investors are more informed or sophisticated in general than individual/retail investors. Prior studies such as Lakonishok, Shleiler, and Vishny (1992) document that institutional investors hold more than 50% of total market capitalization and trade almost 70% of daily volume in the U.S. stock market. Other studies (Hand, 1990; Mayhew, Sarin, and Shastri, 1995; Hendershott, Livdan, and Schurhoff, 2015) show that institutional investors are informed traders owing to their sophistication, lower financial constraints, economies of scale in information collection, and superior access to information. We thus focus on the trading behavior of short-term institutional investors, as these investors are more aggressive in collecting information to form their portfolios (Ali et al., 2004; Hirshleifer, Hsu, and Li, 2016).

To examine the issue, we utilize data on institutional ownership (*IO*). We first construct portfolios by sorting on the change in *short-term* institutional ownership (denoted by *dSIO*). Short-term institutional investors are institutional investors who are categorized as "transient (TRA)" by Bushee (1998, 2001).[19] Transient institutional investors can be identified based on each investor's quarterly position in a specific stock as a percentage of the total number of shares outstanding. The relevant variables are available from the Thomson Reuters Institutional Holdings (13F) database. For each investor-stock pair in each quarter, we calculate the change in short-term institutional ownership from the prior quarter to the current quarter. We then obtain the average of the changes across all short-term institutional investors (*dSIO*) for each firm in each quarter, and sort the component firms by this average value, splitting them into four equal-sized portfolios. We focus on the top quartile (*High* group) and the bottom quartile (*Low* group).

We estimate Eq. (8) for each of the two (*High* and *Low*) groups and present the results in Panel A of Table 11. To save space, we report only the results based on *ANPAT* in a contemporaneous setting ($l = 0$).[20] The panel shows that when the dependent variable is Ω, the coefficients on *ANPAT* in the *High* group is positive and significant at the 1% level, but that in the *Low* group is, albeit positive, not significant. The Chi-square statistic indicates that the null hypothesis [that the difference in the coefficients between the two groups (*High* - *Low*) is zero] is rejected. The result is similar when Π_g is used as the dependent variable. This suggests that the effect of patent news on informed trading is more pronounced among firms that are more subject to larger (positive) changes in institutional ownership, especially

[19] We use Bushee's classification (http://acct.wharton.upenn.edu/faculty/bushee/IIvars.html#mgrno), which includes DED (dedicated), QIX (quasi-indexer), and TRA (transient) based on Bushee (2001) and Bushee and Noe (2000). We thus define the TRA group institutions as short-term institutional investors.

[20] When *ANCITE*, *AVAL*, and other lead orders ($l = 1$ and 2) are used, we obtain consistent results.

because transient institutional investors change their holdings promptly based on the relevant information. That is, all else being equal, we observe more intensive informed trading based on the patent news when short-term institutional investors react aggressively to a given level of information.

Our second analysis is based on the historical pattern of institutional investors' reactions to firm-level patent records. When some, more sophisticated, institutional investors reacted more aggressively to a specific firm's patent news in the *past*, it is likely because this firm's patents are more value-relevant and thus these investors have paid more attention to the firm's patenting activities. In that case, the news about more valuable patents of the firm in the *current* period would lead to more intensive informed trading. To test this hypothesis, for each firm in each quarter, we calculate the correlation between the change in $ANPAT$ (denoted by $dANPAT$) and the average of changes in short-term institutional investors' positions ($dSIO$) over the eight quarters in the past (quarters $q-1$ to $q-8$). We sort component stocks on this correlation each quarter, and then estimate Eq. (8) for the top quartile (*High* group) and the bottom quartile (*Low* group) separately.

The result is reported in Panel B of Table 11. We first find that, for the *High* group, the coefficient on $ANPAT$ is positive and significant, regardless of whether the dependent variable is Ω or Π_g. For the *Low* group, while the coefficient on $ANPAT$ is positive, it is smaller and insignificant. In either of the two cases in Panel B, therefore, the Chi-square tests show that the coefficient is significantly larger in the *High* group. This is consistent with the hypothesis that the effect of patent news on informed trading is stronger when short-term institutional investors reacted more aggressively to patent news in the past. In sum, the above pattern suggests that the causal relations between patent news and informed trading observed above are caused mainly by short-term institutional investors.

6. Cross-Firm Effects of Patent News on Informed Trading in Rival Firms

While obtaining patent approvals or citations is good news for a firm (a 'focal' firm), it could be bad news for other competing firms ('rival firms') due to the exclusivity of patent rights, especially if they are the nearest rivals to the focal firm. If informed investors interpret patent-related (good) news to a firm as bad news to its rival firms, one would expect that they use the news in trading shares of the rival firms. Therefore, our last questions to be answered are whether market participants who follow its rival firms react to the news in a manner consistent with the above conjecture.

To investigate this possibility, we select rival firms as follows. For each focal firm which obtains patents/citations in each quarter, its rival firms are matched based on the product similarity score computed by Hoberg and Phillips (HP) (2010, 2016), which is available from 1996. Since the HP score is calculated on an annual basis, the score is assumed to be constant over the four quarters within a year. For a matched pair (focal firm i and rival firm j), $Ratio\_NPAT = \frac{(adj\text{-}NPAT_j\, -\, adj\text{-}NPAT_i)}{(adj\text{-}NPAT_j\, +\, adj\text{-}NPAT_i)}$ and $Ratio\_NCITE = \frac{(adj\text{-}NCITE_j\, -\, adj\text{-}NCITE_i)}{(adj\text{-}NCITE_j\, +\, adj\text{-}NCITE_i)}$ are computed each quarter, and then the nearest three rival firms are selected (based on the HP score) for a focal firm after restricting that each of the two ratios ($Ratio\_NPAT$ and $Ratio\_NCITE$) is equal to or smaller than -0.8. The sample includes NYSE/AMEX-listed ordinary common stocks (SHRCD = 10 or 11 in CRSP) over the 64 quarters (1996:Q1-2010:Q4). The regression results from using the matched rival firms are reported in Panels A and B in Table 12.[21]

Note that by construction the sample for competitors in Panels A and B still includes some firms that have non-zero patents (although the number of patents is relatively smaller). Thus, the coefficient on $ANPAT$ cannot be negatively significant. The only feasible question here is whether $ANPAT$ is positively related to Ω or Π_g (i.e., whether informed buying activities exist in the rival firms). However, the results exhibit a sharp contrast with those for the focal firms: the coefficient on $ANPAT$ is never positively significant, regardless of the lead order (l = 0, 1, 2) or the dependent variable (Ω in Panel A or Π_g in Panel B) This demonstrates that the positive relations between the patent-related measures and the informed trading measures for the focal firms observed in the previous sections are not driven by a factor that influences all firms within the same product lines.

A more interesting question however is whether investors interpret the information as bad news and trade shares of rival firms accordingly, when patent-related (good) news arrives in a focal firm. Because the conditional measure of informed trading on bad news, π_b, is available, we can look into this aspect. To test the potential presence of informed selling in the rival firms, for each firm we construct the (logit-transformed) measure of informed selling on bad news as another dependent variable: that is, $\Pi_b = \ln\left(\frac{\pi_b^Q}{1-\pi_b^Q}\right)$, where π_b^Q is defined similarly to

[21]Given the two constraints (on the ratio and the score) in selecting the sample, each focal firm is matched with zero to three nearest rival firms in each quarter.

π_g^Q as described in Section 2. For this experiment, we include both the focal firms and their matched rival firms in the sample.[22] To distinguish the rival firms from the focal firms, we use an indicator variable, I_{rival}, which equals one if an observation is a rival firm and zero otherwise. We report the results in Panels C and D of Table 12.

Specification (i) in Panel C shows that $ANPAT$ itself is not significantly associated with the measure of informed trading on bad news, Π_b. However, when $ANPAT$ is interacted with the indicator variable, I_{rival}, the coefficient on $ANPAT$*I_{rival} is positively significant at the 1% level. This suggests that investors indeed interpret the information about patent grants to a focal firm as bad news for its rival firms and hence sell (or sell short) shares of the rival firms on the news. Interestingly, the informed selling on bad news in the rival firms occurs only in the current period, as the coefficient of the interaction term is not significant in specification (ii) or (iii). The short-lived cross-firm effects (i.e., informed selling) in the rival firms (compared to informed buying in the focal firms observed in the previous sections) imply that informed investors generally place lower weight on the potential negative effect of patents granted to a focal firm on the future cash flows of its rival firms. Another reason for the weaker results is attributable to the fact that for a focal firm in a given quarter there can be multiple rival firms, which would make the cross-firm effects less salient over time.

When we use $ANCITE$ as the innovation measure in Panel D, the patterns are similar. We again find a strong cross-firm effect of corporate innovation on informed trading in the rival firms, but in the contemporaneous specification only. Given that the standard deviation (untabulated) of $ANCITE$ for the sample firms included in specification (iv) of Panel D is 1.293, a one-standard-deviation increase in $ANCITE$ causes informed selling (Π_b) to decrease by (insignificant) 0.017 for the forcal firms (e.g., for $I_{rival} = 0$). However, the same increase in $ANCITE$ leads to (significantly) higher Π_b by 0.295 for the rival firms (e.g., for $I_{rival} = 1$), which is equivalent to a 15.8% increase (in absolute terms) relative to the sample average (-1.866) of Π_b. On balance, the results in the two panels confirm that the cross-firm effects in patenting activities do exist, and market participants interpret the information as bad news and trade shares of the rival firms at least in the current period when they receive (good) patent-related news for the focal firms.

[22] For a focal firm, when no rival firm is matched under the two constraints, the focal firm is excluded from the sample in Panels C and D to avoid any confounding effects.

7. Conclusion

Despite the fact that intellectual property owned by a firm has long been recognized as an important determinant of success and sustainability of the firm, the channel though which patenting activities are reflected in stock prices or whether in practice investors trade securities of the firm or its rival firms based on such information remains unexplored in the literature. It is partly because of difficulties in identifying appropriate empirical proxies for informed trading and innovation performance. To examine these issues, we construct (or obtain) patent-news measures as well as high-frequency-based informed trading measures.

The results from portfolio analyses, Fama-MacBeth (1973) cross-sectional regressions, and pooled regressions show that informed trading increases significantly with patent news in the quarter during which firms are granted with more, better, and higher-valued patents. Patent news also predicts informed trading up to two quarters ahead (albeit to a lesser degree), suggesting that it takes time before some investors react to publicly available information. Our results are robust to controlling for the industry and year fixed effects, using alternative proxies, and including the firms with no patent. These findings altogether provide direct evidence that patenting performance is an important determinant and predictor of informed trading. We address endogeneity issues by conducting DiD regressions using an exogenous policy shock as well as 2SLS estimation after devising two instrumental variables.

We then utilize institutional ownership data to show that the effect of patent news on informed trading is more pronounced when transient institutional investors react aggressively to patent-related information; and the effect of patent news on informed trading is stronger in the current period when short-term institutional investors reacted more positively to patent-related information in the past. These results provide evidence that the trading behavior of aggressive transient institutional investors drives the relation between patent news and informed trading. In the last experiment, we examine whether there is any cross-firm effect of patent-related news on informed trading in rival firms. We find evidence that investors interpret patent news to focal firms as bad news to their rival firms and trade shares of the rival firms accordingly. However, the cross-firm effects exist only in the current period.

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Table 1
Descriptive Statistics for Key Variables

This table reports the descriptive statistics [average of quarterly mean, median, standard deviation (*STD*), skewness, and kurtosis] for the key variables. The cross-sectional value for each of the six statistics is first calculated each quarter and then the time-series average of those statistics is reported. The informed trading measures are defined as follows. Ω: the quarterly average of ω^M, which is the monthly average of daily values in $\omega^D = \lambda^{FV} * DOIMB^D$, where λ^{FV} is the monthly price-impact parameter estimated using intradaily dollar order flows (in $million) within the previous month (month *m-1*) based on the Foster and Viswanathan (1993) model, and $DOIMB^D$ is the daily dollar-value order imbalance (in $million) in the current month (month *m*) computed as the daily aggregated buyer-initiated dollar volume (obtained by adding intradaily buyer-initiated dollar volume within each day) minus the daily aggregated seller-initiated dollar volume (obtained by adding intradaily seller-initiated dollar volume within each day); π_g^Q: the quarterly average of values in π_g^M, which is the monthly average of daily values in π_g, which is in turn the daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that a good-news information event occurs on a given day; Π_g: the logit-transform of π_g^Q [i.e., $\ln\left(\frac{\pi_g^Q}{1-\pi_g^Q}\right)$], where π_g^Q is the quarterly average of values in π_g^M. To process order flows used in the above variables, intradaily trades and quotes from ISSM/TAQ are matched (to classify into a buyer- or seller-initiated category) based on the Lee and Ready (1991) algorithm up to December 2006 and on the Holden and Jacobsen (2014) algorithm from January 2007 to December 2010. Other variables are defined as follows. *NPAT*: the quarterly (unadjusted) number of granted patents; *ANPAT*: the natural logarithm of one plus quarterly *adj-NPAT*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of patents granted to firms that are granted at least one patent in the class in the quarter is calculated; (ii) the focal firm's patent number in the class in the quarter is scaled by the average number calculated in step (i) to get the adjusted patent counts in that class; and (iii) all the adjusted patent counts are added across all classes in the quarter to obtain *adj-NPAT* for the firm]; *NCITE*: the quarterly (unadjusted) number of patent citations received within the following three years; *ANCITE*: the natural logarithm of one plus quarterly *adj-NCITE*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of subsequent citations received (up to 2010) by the patents granted to the firms in this class is calculated; (ii) the number of subsequent citations received (up to 2010) by the patent granted to the firm in the class in the quarter is scaled by the average number of citations calculated in step (i) to get the adjusted patent citations in the class; and (iii) all the adjusted patent citations are added across all classes in the quarter to obtain *adj-NCITE* for the firm]; *VAL*: the (inflation-adjusted) value of patents (in $1,000) aggregated across all patents granted to the firm in each quarter, as used in Kogan, Papanikolaou, Seru, and Stoffman (2015) (obtained from Dimitris Papanikolaou's website); *AVAL*: the natural logarithm of one plus *VAL*; *R&D*: the ratio (in %) of quarterly research and development expenses (in $million) to quarter-end assets (in $million), and 0 if the expense is missing; *dIH*: the quarterly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding; *ROA*: the ratio (in %) of quarterly net income (in $million) to quarter-end assets (in $million), and 0 if missing; *RVOLA*: the quarterly average of monthly return volatility (in %), for which the monthly standard deviation of daily returns within a month is computed; *BTM*: the ratio of quarter-end book value (in $million) to quarter-end market capitalization (in $million); and *NANA*: the number of analysts following a firm. The sample period is the past 84 quarters (1990:Q1-2010:Q4) for NYSE/AMEX-listed firms. The sample includes only the firms that have positive values in the number of patents (*NPAT*). Ordinary common stocks only (SHRCD = 10 or 11 in CRSP) are used. The average number of firms used each quarter is 269.20. The total number of observations (firm-quarters) is 22,613.

Descriptive Statistics for Key Variables					
Variables	Mean	Median	STD	Skewness	Kurtosis
Ω	0.096	0.051	0.260	4.57	58.55
π_g^Q	0.282	0.254	0.181	0.85	1.03
Π_g	-1.482	-1.128	2.735	-5.36	54.37
NPAT	14.84	3.44	37.79	5.65	45.76
NCITE	207.20	32.40	643.09	6.60	59.67
VAL	279,232.7	24,936.0	782,087.6	4.72	27.97
ANPAT	1.030	0.768	0.822	1.18	1.01
ANCITE	2.705	2.541	1.529	0.67	1.90
AVAL	10.034	10.008	2.229	0.00	-0.42
R&D	1.060	0.319	1.905	4.62	39.70
dIH	-0.001	0.000	7.805	-0.70	124.00
ROA	0.840	1.294	4.679	-4.62	55.83
RVOLA	2.348	2.072	1.085	2.16	8.51
BTM	0.514	0.441	0.374	2.51	14.61
NANA	10.021	8.595	8.177	0.67	-0.35

Table 2
Statistics for Patent-Related Variables by Industry

This table reports the quarterly statistics for innovation-related variables. Each quarter the cross-sectional average is first calculated by industry and then the time-series average of quarterly values over the 84 quarters is reported. Industries are classified based on the Fama-French (FF) 12-industry classification method. *NPAT* is the quarterly (unadjusted) number of granted patents. *NCITE* is the quarterly (unadjusted) number of patent citations received by the end of 2010. *VAL* is the (inflation-adjusted) economic value of patents (in $1,000) aggregated across all patents granted to the firm in each quarter, which is used in Kogan et al. (2015). The sample period is the past 84 quarters (1990:Q1-2010:Q4) for NYSE/AMEX-listed firms. Ordinary common stocks only (SHRCD = 10 or 11 in CRSP) are used.

Quarterly Statistics of Corporate Innovation Variables by Industry

FF-Class.	Industry Symbol	Detailed Industry Description	Notation for Dummies	Avg. #Firms Included Each Quarter	For Firms with Non-Zero Patents Only				
					Avg. #Firms	Proportion	NPAT	NCITE	VAL
1	NoDur	Consumer Non-Durables: Food, Tobacco, Textiles, Apparel, Leather, Toys	IDUM01	114.7	16.0	0.140	3.59	25.16	132,081.0
2	Durbl	Consumer Durables: Cars, TV's, Furnitue, Household Appliances	IDUM02	55.1	18.6	0.337	15.29	184.39	342,304.3
3	Manuf	Manufacturing: Machinery, Trucks, Planes, Office Furniture, Paper, Commercial Printing	IDUM03	260.9	81.4	0.312	10.52	111.19	121,931.2
4	Enrgy	Oil, Gas, and Coal Extraction and Products	IDUM04	110.1	10.5	0.096	12.16	171.98	545,641.9
5	Chems	Chemicals and Allied Products	IDUM05	63.9	25.3	0.397	14.29	139.99	251,866.1
6	BusEq	Business Equipment: Computers, Software, and Electronic Equipment	IDUM06	185.1	54.3	0.293	26.65	460.02	328,489.9
7	Telcm	Telephone and Television Transmission	IDUM07	35.0	4.0	0.114	53.05	1,257.24	1,614,406.4
8	Utils	Utilities	IDUM08	100.7	1.8	0.018	1.22	12.88	10,129.5
9	Shops	Wholesale, Retail, and Some Services (Laundries, Repair Shops)	IDUM09	187.4	7.3	0.039	3.12	44.86	42,778.6
10	Hlth	Healthcare, Medical Equipment, and Drugs	IDUM10	123.3	26.1	0.212	15.79	278.33	655,436.2
11	Money	Finance	IDUM11	272.5	5.1	0.019	2.55	36.34	39,142.2
12	Other	Other Indus.: Mines, Construction, Building Materials, Transport., Hotels, Business Services, Entertainment	IDUM12	241.9	11.8	0.049	2.60	30.65	33,969.4
		Quarterly Total across Industries		1,750.6	262.3	0.150	160.83	2,753.02	4,118,176.8

Table 3
Averages of the Informed Trading Measure for Portfolios Formed by Sorting on Patent-Related Measures

This table reports the averages of the informed trading measures (Ω and π_g^Q) for the portfolios formed by one of the three innovation measures. We sort all component stocks into five portfolios based on the number of granted patents (Panel A), the number of citations (Panel B), or the economic value of patents (Panel C) as of the previous quarter (i.e., $ANPAT_{t-1}$, $ANCITE_{t-1}$, or $AVAL_{t-1}$). We next calculate the current quarter (quarter *t*)'s cross-sectional mean of the informed trading measure (Ω or π_g^Q) in each portfolio, and then the time-series average of the cross-sectional means over the sample period is reported for each portfolio. Ω is the quarterly average of ω^M, which is the monthly average of daily values in $\omega^D = \lambda^{FV} * DOIMB^D$, where λ^{FV} is the monthly price-impact parameter estimated using intradaily dollar order flows (in $million) within the previous month (month *m-1*) based on the Foster-Viswanathan (1993) model, and $DOIMB^D$ is the daily dollar-value order imbalance (in $million) in the current month (month *m*) computed as the daily aggregated buyer-initiated dollar volume (by adding intradaily buyer-initiated dollar volume within each day) minus the daily aggregated seller-initiated dollar volume (by adding intradaily seller-initiated dollar volume within each day). π_g^Q is the quarterly average of values in π_g^M, which is the monthly average of daily values in π_g, which is in turn the daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that a good-news information event occurs on a given day. To process order flows used in the above variables, intradaily trades and quotes from ISSM/TAQ are matched (to classify into a buyer- or seller-initiated category) based on the Lee and Ready (1991) algorithm up to December 2006 and on the Holden and Jacobsen (2014) algorithm from January 2007 to December 2010. *ANPAT* is the natural logarithm of one plus quarterly *adj-NPAT*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of patents granted to firms that are granted at least one patent in the class in the quarter is calculated; (ii) the focal firm's patent number in the class in the quarter is scaled by the average number calculated in step (i) to get the adjusted patent counts in that class; and (iii) all the adjusted patent counts are added across all classes in the quarter to obtain *adj-NPAT* for the firm]. *ANCITE* is the natural logarithm of one plus quarterly *adj-NCITE*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of subsequent citations received (up to 2010) by the patents granted to the firms in this class is calculated; (ii) the number of subsequent citations received (up to 2010) by the patent granted to the firm in the class in the quarter is scaled by the average number of citations calculated in step (i) to get the adjusted patent citations in the class; and (iii) all the adjusted patent citations are added across all classes in the quarter to obtain *adj-NCITE* for the firm]. *AVAL* is the natural logarithm of one plus the quarterly *VAL*, which is the economic value of patents (in $1,000) aggregated across all patents granted to the firm in each quarter, as used in Kogan et al. (2015) (obtained from Dimitris Papanikolaou's website). The heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics computed based on Newey and West (1987, 1994) in the lower part of each panel is the statistic to test the null hypothesis that the value for the (*High – Low*) portfolio is zero. The sample period is the past 84 quarters (1990:Q1-2010:Q4) for NYSE/AMEX-listed firms that have positive values in the number of granted patents or in the number of patent citations. Ordinary common stocks only (SHRCD = 10 or 11 in CRSP) are used. *Avg Obs* is the time-series average of the number of component stocks used in each portfolio in each quarter.

Averages of $\boldsymbol{\Omega}$ and $\boldsymbol{\pi_g^Q}$ for Portfolios Sorted on Innovation Measures						
	Panel A: Sorted on ANPAT		Panel B: Sorted on ANCITE		Panel C: Sorted on AVAL	
Group	Avg. of $\boldsymbol{\Omega}$	Avg. of $\boldsymbol{\pi_g^Q}$	Avg. of $\boldsymbol{\Omega}$	Avg. of $\boldsymbol{\pi_g^Q}$	Avg. of $\boldsymbol{\Omega}$	Avg. of $\boldsymbol{\pi_g^Q}$
1 Low	0.0589	0.2467	0.0563	0.2472	0.0275	0.2088
2	0.0613	0.2590	0.0599	0.2617	0.0495	0.2592
3	0.0727	0.2711	0.0760	0.2767	0.0745	0.2834
4	0.0952	0.2910	0.0960	0.2956	0.1070	0.3011
5 High	0.1884	0.3185	0.1994	0.3242	0.2118	0.3318
(High - Low)	0.1295	0.0718	0.1431	0.0770	0.1844	0.1230
t-value	*6.22*	*9.22*	*6.29*	*9.05*	*7.26*	*11.21*
Avg Obs	50.2		47.6		51.5	

Table 4

Quarterly Cross-Sectional Regressions Using the Number of Granted Patents (*ANPAT*)

This table reports the results of quarterly Fama-MacBeth (1973) cross-sectional regressions using the number of granted patents (*ANPAT*) for NYSE/AMEX firms over the 84 quarters (1990:Q1-2010:Q4). The sample includes only the firms that have positive values in the number of patents, and ordinary common stocks (SHRCD = 10 or 11 in CRSP) only are used. The dependent variable is Ω in Panel A and Π_g in Panel B. The dependent variables used in the two panels are defined as follows: Ω: the quarterly average of ω^M, which is the monthly average of daily values in $\omega^D = \lambda^{FV} * DOIMB^D$, where λ^{FV} is the monthly price-impact parameter estimated using intradaily dollar order flows (in $million) within the previous month (month *m-1*) based on the Foster and Viswanathan (1993) model, and $DOIMB^D$ is the daily dollar-value order imbalance (in $million) in the current month (month *m*) computed as the daily aggregated buyer-initiated dollar volume (obtained by adding intradaily buyer-initiated dollar volume within each day) minus the daily aggregated seller-initiated dollar volume (obtained by adding intradaily seller-initiated dollar volume within each day); Π_g: the logit-transform of π_g^Q [i.e., $\ln\left(\frac{\pi_g^Q}{1-\pi_g^Q}\right)$], where π_g^Q is the quarterly average of values in π_g^M, which is in turn the monthly average of daily values in π_g [π_g is the daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that a good-news information event occurs on a given day]. To process order flows used in the above variables, intradaily trades and quotes from ISSM/TAQ are matched (to classify into a buyer- or seller-initiated category) based on the Lee and Ready (1991) algorithm up to December 2006 and on the Holden and Jacobsen (2014) algorithm from January 2007 to December 2010. The explanatory variables are defined as follows: *ANPAT*: the natural logarithm of one plus quarterly *adj-NPAT*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of patents granted to firms that are granted at least one patent in the class in the quarter is calculated; (ii) the focal firm's patent number in the class in the quarter is scaled by the average number calculated in step (i) to get the adjusted patent counts in that class; and (iii) all the adjusted patent counts are added across all classes in the quarter to obtain *adj-NPAT* for the firm]; *R&D*: the ratio (in %) of quarterly research and development expenses (in $million) to quarter-end assets (in $million), and 0 if the expense is missing; *dIH*: the quarterly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding; *ROA*: the ratio (in %) of quarterly net income (in $million) to quarter-end assets (in $million), and 0 if missing; *RVOLA*: the quarterly average of monthly return volatility (in %), for which the monthly standard deviation of daily returns within a month is computed; *BTM*: the ratio of quarter-end book value (in $million) to quarter-end market capitalization (in $million); and *NANA*: the number of analysts following a firm; and *IDUM*: a vector of industry dummy variables (*IDUM01-IDUM12*) as defined in Table 2 (*IDUM12* is the base case and thus excluded in the regressions). The letter *l* is the lead order in the dependent variable: *l* = 0, 1, and 2 mean that the dependent variable in the regressions is contemporaneous, led by a quarter, and led by two quarters, respectively. 'Yes' indicates that the 11 dummy variables are included in the quarterly cross-sectional regressions. The values in the first row for each explanatory variable are time-series averages of coefficients obtained from the quarterly cross-sectional regressions, and the values italicized in the second row of each variable are heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics computed based on Newey and West (1987, 1994). All coefficients are multiplied by 10. *Avg Adj-Rsqr* is the average of adjusted R-squared from quarterly individual regressions. *Avg Obs* is the average number of companies used each quarter in the cross-sectional regressions. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

(Table 4: continued)

	Panel A: Cross-Sectional Regressions with Dep. Var. = $\boldsymbol{\Omega}$						Panel B: Cross-Sectional Regressions with Dep. Var. = $\boldsymbol{\Pi_g}$					
Expla. Vars.	(i) *l = 0*		(ii) *l = 1*		(iii) *l = 2*		(iv) *l = 0*		(v) *l = 1*		(vi) *l = 2*	
Intercept	-0.007		0.168		0.132		-18.293	**	-8.977	**	-15.119	**
	-0.03		*0.87*		*0.70*		*-10.23*		*-6.40*		*-7.76*	
ANPAT	0.496	**	0.474	**	0.462	**	1.923	**	1.105	**	1.291	**
	3.83		*3.26*		*3.68*		*4.81*		*3.38*		*3.64*	
R&D	0.021		0.027		0.010		-0.421		-0.036		-0.314	
	1.09		*1.49*		*0.36*		*-1.37*		*-0.11*		*-0.89*	
dIH	0.109		0.105		0.288		2.818		-0.788		4.640	
	0.86		*1.25*		*0.85*		*0.87*		*-0.27*		*1.26*	
ROA	0.041	**	0.037	**	0.027	**	0.354	*	0.085		0.126	
	3.84		*4.30*		*3.00*		*2.31*		*1.13*		*1.12*	
RVOLA	0.180	**	0.112	*	0.108	*	0.277		-3.999	**	-1.738	**
	2.98		*2.34*		*2.23*		*0.59*		*-9.32*		*-4.02*	
BTM	-0.470	**	-0.470	**	-0.469	**	-2.297	*	-0.405		-0.584	
	-3.47		*-3.75*		*-3.22*		*-2.24*		*-0.60*		*-0.98*	
NANA	0.027	**	0.025	*	0.026	**	0.239	**	0.229	**	0.256	**
	2.68		*2.34*		*3.02*		*3.10*		*2.86*		*3.13*	
IDUM	Yes		Yes		Yes		Yes		Yes		Yes	
Avg Adj-Rsqr	0.163		0.168		0.151		0.071		0.096		0.073	
Avg Obs	261.4		260.3		256.5		262.0		254.1		250.5	

Table 5

Quarterly Cross-Sectional Regressions Using the Number of Patent Citations (*ANCITE*)

This table reports the results of quarterly Fama-MacBeth (1973) cross-sectional regressions using the number of patent citations (*ANCITE*) for NYSE/AMEX firms over the 84 quarters (1990:Q1-2010:Q4). The sample includes only the firms that have positive values in the number of patent citations, and ordinary common stocks (SHRCD = 10 or 11 in CRSP) only are used. The dependent variable is Ω in Panel A and Π_g in Panel B. The dependent variables used in the two panels are defined as follows: Ω: the quarterly average of ω^M, which is the monthly average of daily values in $\omega^D = \lambda^{FV} * DOIMB^D$, where λ^{FV} is the monthly price-impact parameter estimated using intradaily dollar order flows (in $million) within the previous month (month *m-1*) based on the Foster and Viswanathan (1993) model, and $DOIMB^D$ is the daily dollar-value order imbalance (in $million) in the current month (month *m*) computed as the daily aggregated buyer-initiated dollar volume (obtained by adding intradaily buyer-initiated dollar volume within each day) minus the daily aggregated seller-initiated dollar volume (obtained by adding intradaily seller-initiated dollar volume within each day); Π_g: the logit-transform of π_g^Q [i.e., $\ln\left(\frac{\pi_g^Q}{1-\pi_g^Q}\right)$], where π_g^Q is the quarterly average of values in π_g^M, which is in turn the monthly average of daily values in π_g [π_g is the daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that a good-news information event occurs on a given day]. To process order flows used in the above variables, intradaily trades and quotes from ISSM/TAQ are matched (to classify into a buyer- or seller-initiated category) based on the Lee and Ready (1991) algorithm up to December 2006 and on the Holden and Jacobsen (2014) algorithm from January 2007 to December 2010. The explanatory variables are defined as follows: *ANCITE*: the natural logarithm of one plus quarterly *adj-NCITE*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of subsequent citations received (up to 2010) by the patents granted to the firms in this class is calculated; (ii) the number of subsequent citations received (up to 2010) by the patent granted to the firm in the class in the quarter is scaled by the average number of citations calculated in step (i) to get the adjusted patent citations in the class; and (iii) all the adjusted patent citations are added across all classes in the quarter to obtain *adj-NCITE* for the firm]. Other variables are defined in the previous tables. The letter *l* is the lead order in the dependent variable: *l* = 0, 1, and 2 mean that the dependent variable in the regressions is contemporaneous, led by a quarter, and led by two quarters, respectively. 'Yes' indicates that the 11 industry dummy variables are included in the quarterly cross-sectional regressions. The values in the first row for each explanatory variable are time-series averages of coefficients obtained from the quarterly cross-sectional regressions, and the values italicized in the second row of each variable are heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics computed based on Newey and West (1987, 1994). All coefficients are multiplied by 10. *Avg Adj-Rsqr* is the average of adjusted R-squared from quarterly individual regressions. *Avg Obs* is the average number of companies used each quarter in the cross-sectional regressions. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

(Table 5: continued)

Expla. Vars.	Panel A: Cross-Sectional Regressions with Dep. Var. = $\boldsymbol{\Omega}$ (i) $l = 0$		(ii) $l = 1$		(iii) $l = 2$		Panel B: Cross-Sectional Regressions with Dep. Var. = $\boldsymbol{\Pi_g}$ (iv) $l = 0$		(v) $l = 1$		(vi) $l = 2$	
Intercept	-0.329		-0.133		-0.105		-18.422	**	-10.410	**	-14.835	**
	-1.16		*-0.52*		*-0.44*		*-8.14*		*-6.13*		*-6.46*	
ANCITE	0.260	**	0.236	**	0.224	**	0.720	*	0.663	**	0.543	*
	3.89		*3.32*		*3.96*		*2.25*		*3.13*		*2.17*	
R&D	0.013		0.022		-0.014		-0.334		0.092		-0.408	
	0.67		*1.25*		*-0.44*		*-1.41*		*0.30*		*-1.25*	
dIH	0.120		0.133		0.368		6.279		-1.496		5.928	
	0.89		*1.52*		*0.99*		*1.33*		*-0.51*		*1.32*	
ROA	0.042	**	0.040	**	0.029	**	0.262	**	0.092		0.115	
	3.81		*4.60*		*3.05*		*2.98*		*1.33*		*0.68*	
RVOLA	0.173	**	0.102	*	0.077		0.248		-3.789	**	-2.254	**
	2.94		*2.27*		*1.76*		*0.57*		*-8.15*		*-3.25*	
BTM	-0.461	**	-0.470	**	-0.437	**	-2.005		-0.297		-0.197	
	-3.33		*-3.68*		*-2.93*		*-1.87*		*-0.49*		*-0.25*	
NANA	0.031	**	0.029	**	0.033	**	0.187	**	0.196	**	0.263	**
	2.74		*2.60*		*4.13*		*3.05*		*2.71*		*2.66*	
IDUM	Yes		Yes		Yes		Yes		Yes		Yes	
Avg Adj-Rsqr	0.149		0.134		0.137		0.072		0.108		0.070	
Avg Obs	250.1		248.8		245.3		250.6		243.9		239.0	

Table 6

Quarterly Cross-Sectional Regressions Using the Economic Value of Patents (*AVAL*)

This table reports the results of quarterly Fama-MacBeth (1973) cross-sectional regressions using the economic value of patents (*AVAL*) for NYSE/AMEX firms over the 84 quarters (1990:Q1-2010:Q4). The sample includes only the firms that have positive values in the number of patent citations, and ordinary common stocks (SHRCD = 10 or 11 in CRSP) only are used. The dependent variable is Ω in Panel A and Π_g in Panel B. The dependent variables used in the two panels are defined as follows: Ω: the quarterly average of ω^M, which is the monthly average of daily values in $\omega^D = \lambda^{FV} * DOIMB^D$, where λ^{FV} is the monthly price-impact parameter estimated using intradaily dollar order flows (in $million) within the previous month (month *m-1*) based on the Foster and Viswanathan (1993) model, and $DOIMB^D$ is the daily dollar-value order imbalance (in $million) in the current month (month *m*) computed as the daily aggregated buyer-initiated dollar volume (obtained by adding intradaily buyer-initiated dollar volume within each day) minus the daily aggregated seller-initiated dollar volume (obtained by adding intradaily seller-initiated dollar volume within each day); Π_g: the logit-transform of π_g^Q [i.e., $\ln\left(\frac{\pi_g^Q}{1-\pi_g^Q}\right)$], where π_g^Q is the quarterly average of values in π_g^M, which is in turn the monthly average of daily values in π_g [π_g is the daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that a good-news information event occurs on a given day]. To process order flows used in the above variables, intradaily trades and quotes from ISSM/TAQ are matched (to classify into a buyer- or seller-initiated category) based on the Lee and Ready (1991) algorithm up to December 2006 and on the Holden and Jacobsen (2014) algorithm from January 2007 to December 2010. The explanatory variables are defined as follows. *AVAL*: the natural logarithm of one plus the quarterly *VAL*, which is the economic value of patents (in $1,000) aggregated across all patents granted to the firm in each quarter, as used in Kogan, Papanikolaou, Seru, and Stoffman (2015) (obtained from Dimitris Papanikolaou's website). Other variables are defined in the previous tables. The letter *l* is the lead order in the dependent variable: *l* = 0, 1, and 2 mean that the dependent variable in the regressions is contemporaneous, led by a quarter, and led by two quarters, respectively. 'Yes' indicates that the 11 industry dummy variables are included in the quarterly cross-sectional regressions. The values in the first row for each explanatory variable are time-series averages of coefficients obtained from the quarterly cross-sectional regressions, and the values italicized in the second row of each variable are heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics computed based on Newey and West (1987, 1994). All coefficients are multiplied by 10. *Avg Adj-Rsqr* is the average of adjusted R-squared from quarterly individual regressions. *Avg Obs* is the average number of companies used each quarter in the cross-sectional regressions. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

(Table 6: continued)

	Panel A: Cross-Sectional Regressions with Dep. Var. = $\boldsymbol{\Omega}$			Panel B: Cross-Sectional Regressions with Dep. Var. = $\boldsymbol{\Pi_g}$		
Expla. Vars.	(i) *l = 0*	(ii) *l = 1*	(iii) *l = 2*	(iv) *l = 0*	(v) *l = 1*	(vi) *l = 2*
Intercept	-2.273 **	-1.927 **	-1.755 **	-35.565 **	-19.628 **	-29.833 **
	-3.51	*-3.03*	*-3.07*	*-10.86*	*-7.42*	*-8.93*
AVAL	0.270 **	0.244 **	0.228 **	1.730 **	1.268 **	1.524 **
	4.56	*3.93*	*4.25*	*6.61*	*4.83*	*5.05*
R&D	0.018	0.028	0.006	-0.615 *	-0.029	-0.292
	1.11	*1.89*	*0.22*	*-2.35*	*-0.10*	*-1.00*
dIH	0.138	-0.006	0.365	3.634	-1.793	4.378
	1.13	*-0.09*	*1.09*	*1.08*	*-0.52*	*1.13*
ROA	0.026 **	0.029 **	0.014 *	0.171 *	-0.011	0.082
	2.70	*4.09*	*2.19*	*2.05*	*-0.14*	*0.84*
RVOLA	0.176 **	0.126 **	0.105 *	0.992 *	-4.091 **	-1.401 **
	3.33	*2.84*	*2.38*	*2.43*	*-8.53*	*-4.30*
BTM	-0.068	-0.080	-0.118	-0.065	0.732	1.335
	-0.75	*-1.75*	*-1.75*	*-0.09*	*0.83*	*1.51*
NANA	0.009	0.009	0.015 **	0.128	0.074	0.100
	1.35	*0.94*	*2.62*	*1.87*	*1.11*	*1.58*
IDUM	Yes	Yes	Yes	Yes	Yes	Yes
Avg Adj-Rsqr	0.178	0.187	0.180	0.080	0.108	0.075
Avg Obs	269.1	266.6	259.8	269.2	260.5	254.0

Table 7

Pooled Regressions Controlling for Industry and Year Fixed Effects

This table reports the results of pooled regressions using the firms that have positive values in the number of granted patents. NYSE/AMEX-listed ordinary common stocks only (SHRCD = 10 or 11 in CRSP) are used over the 84 quarters (1990:Q1-2010:Q4). The pooled regression results from using the number of granted patents (*ANPAT*), the number of patent citations (*ANCITE*), and the economic value of patents (*AVAL*) are contained in Panels A, B, and C, respectively. The dependent variables used in the three panels are defined as follows: Ω: the quarterly average of ω^M, which is the monthly average of daily values in $\omega^D = \lambda^{FV} * DOIMB^D$, where λ^{FV} is the monthly price-impact parameter estimated using intradaily dollar order flows (in $million) within the previous month (month *m-1*) based on the Foster and Viswanathan (1993) model, and $DOIMB^D$ is the daily dollar-value order imbalance (in $million) in the current month (month *m*) computed as the daily aggregated buyer-initiated dollar volume (obtained by adding intradaily buyer-initiated dollar volume within each day) minus the daily aggregated seller-initiated dollar volume (obtained by adding intradaily seller-initiated dollar volume within each day); Π_g: the logit-transform of π_g^Q [i.e., $\ln\left(\frac{\pi_g^Q}{1-\pi_g^Q}\right)$], where π_g^Q is the quarterly average of values in π_g^M, which is in turn the monthly average of daily values in π_g [π_g is the daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that a good-news information event occurs on a given day]. To process order flows used in the above variables, intradaily trades and quotes from ISSM/TAQ are matched (to classify into a buyer- or seller-initiated category) based on the Lee and Ready (1991) algorithm up to December 2006 and on the Holden and Jacobsen (2014) algorithm from January 2007 to December 2010. The explanatory variables are defined as follows: *ANPAT*: the natural logarithm of one plus quarterly *adj-NPAT*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of patents granted to firms that are granted at least one patent in the class in the quarter is calculated; (ii) the focal firm's patent number in the class in the quarter is scaled by the average number calculated in step (i) to get the adjusted patent counts in that class; and (iii) all the adjusted patent counts are added across all classes in the quarter to obtain *adj-NPAT* for the firm]; *ANCITE*: the natural logarithm of one plus quarterly *adj-NCITE*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of subsequent citations received (up to 2010) by the patents granted to the firms in this class is calculated; (ii) the number of subsequent citations received (up to 2010) by the patent granted to the firm in the class in the quarter is scaled by the average number of citations calculated in step (i) to get the adjusted patent citations in the class; and (iii) all the adjusted patent citations are added across all classes in the quarter to obtain *adj-NCITE* for the firm]; *AVAL*: the natural logarithm of one plus the quarterly *VAL*, which is the economic value of patents (in $1,000) aggregated across all patents granted to the firm in each quarter, as used in Kogan, Papanikolaou, Seru, and Stoffman (2015) (obtained from Dimitris Papanikolaou's website); and *LDV*: one-quarter lagged value of the dependent variable (Ω or Π_g). Other variables are defined in the previous tables. To control for industry fixed effects, industry dummy variables based on the Fama-French 12-industry classification (*IDUM01-IDUM12*: defined in Table 2) are used (*IDUM12* is the base case and thus excluded). To control for year fixed effects, 21 year dummy variables are also used (the dummy for 2010 is excluded). The letter *l* is the lead order in the dependent variable: *l* = 0, 1, and 2 mean that the dependent variable in the regressions is contemporaneous, led by a quarter, and led by two quarters, respectively. 'Yes' indicates that the industry or year dummy variables are included in the regressions. The values in the first row for each explanatory variable are the coefficients from the pooled regressions, and the values italicized in the second row of each variable are within-industry clustered-error-consistent *t*-statistics. All coefficients are multiplied by 10. *Adj-Rsqr* is the adjusted R-squared. *Obs* is the number of observations (firm-quarters) used in the pooled regressions. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

(Table 7: continued)

Panel A: Pooled Regressions with the Number of Granted Patents (ANPAT) (1990Q1-2010Q4)

Explanat. Vars.	Dep. Var. = $\boldsymbol{\Omega}$						Dep. Var. = $\boldsymbol{\Pi_g}$					
	(i) *l* = 0		(ii) *l* = 1		(iii) *l* = 2		(iv) *l* = 0		(v) *l* = 1		(vi) *l* = 2	
Intercept	-0.927	**	-0.826	**	-0.806	**	-21.180	**	-17.020	**	-27.069	**
	-5.79		*-4.83*		*-4.54*		*-11.10*		*-9.72*		*-6.38*	
ANPAT	0.584	**	0.572	**	0.559	**	1.787	**	1.446	**	1.777	**
	3.25		*3.70*		*2.97*		*6.18*		*4.36*		*8.70*	
R&D	0.014		0.025		0.004		-0.532		0.197	*	-0.603	
	0.49		*1.07*		*0.11*		*-1.93*		*2.13*		*-1.83*	
dIH	0.000	**	0.000		0.000		-0.001		-0.001		0.002	**
	-3.01		*-1.31*		*-0.07*		*-0.79*		*-1.21*		*7.02*	
ROA	0.020	*	0.021	*	0.013		0.129	**	0.089	**	0.120	**
	2.32		*2.41*		*1.55*		*4.68*		*4.29*		*4.49*	
RVOLA	0.222	**	0.149	**	0.122	**	0.839	**	-3.257	**	-1.200	**
	4.57		*3.12*		*3.09*		*3.60*		*-6.92*		*-3.12*	
BTM	-0.547	*	-0.567	**	-0.396	*	-2.852	**	0.819	**	-0.014	
	-2.44		*-3.99*		*-2.43*		*-3.74*		*2.86*		*-0.02*	
NANA	0.026	**	0.025	**	0.022	**	0.189	**	0.168	**	0.185	**
	3.52		*2.78*		*3.74*		*3.55*		*3.06*		*3.46*	
LDV	1.554		1.051		1.612		0.292		0.337	*	0.260	*
	1.13		*1.22*		*1.09*		*1.77*		*2.40*		*2.29*	
Industry Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Adj-Rsqr	0.051		0.060		0.047		0.028		0.038		0.030	
Obs	21,865		22,039		21,969		21,172		21,260		20,726	

(Table 7: continued)

Panel B: Pooled Regressions with the Number of Patent Citations (ANCITE) (1990Q1-2010Q4)

	Dep. Var. = $\boldsymbol{\Omega}$						Dep. Var. = $\boldsymbol{\Pi_g}$					
Explanat. Vars.	(i) l = 0		(ii) l = 1		(iii) l = 2		(iv) l = 0		(v) l = 1		(vi) l = 2	
Intercept	-1.030	**	-0.771	**	-0.875	**	-11.565	**	-8.211	**	-22.330	**
	-4.83		*-3.42*		*-4.52*		*-6.11*		*-5.04*		*-6.91*	
ANCITE	0.314	**	0.299	**	0.247	**	0.839	**	0.824	**	0.891	**
	3.39		*3.57*		*4.95*		*4.25*		*4.62*		*4.55*	
R&D	0.005		0.019		-0.016		-0.349		0.358	**	-0.566	
	0.15		*0.73*		*-0.40*		*-1.85*		*5.48*		*-1.45*	
dIH	0.000	**	0.000		0.000		-0.001		-0.001		0.002	**
	-2.93		*-1.81*		*-1.01*		*-0.71*		*-1.30*		*6.02*	
ROA	0.019	*	0.021	*	0.009		0.138	**	0.075	**	0.113	**
	2.25		*2.35*		*1.52*		*5.65*		*2.80*		*3.70*	
RVOLA	0.218	**	0.130	**	0.111	**	0.840	**	-3.493	**	-1.360	**
	4.71		*2.75*		*2.89*		*3.15*		*-7.43*		*-3.49*	
BTM	-0.603	*	-0.648	**	-0.407	**	-3.290	**	0.565		0.065	
	-2.45		*-4.17*		*-2.88*		*-3.49*		*1.75*		*0.10*	
NANA	0.027	**	0.027	**	0.033	**	0.186	**	0.156	**	0.188	**
	3.54		*2.83*		*4.63*		*3.72*		*2.61*		*3.27*	
LDV	1.550		1.047		1.613		0.263		0.319	**	0.285	*
	1.13		*1.22*		*1.11*		*1.85*		*2.91*		*2.51*	
Industry Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Adj-Rsqr	0.049		0.057		0.083		0.027		0.038		0.028	
Obs	20,202		20,351		20,079		19,789		19,936		19,360	

(Table 7: continued)

Panel C: Pooled Regressions with the Value of Patents (AVAL) (1990Q1-2010Q4)

	Dep. Var. = $\boldsymbol{\Omega}$			Dep. Var. = $\boldsymbol{\Pi_g}$		
Explanat. Vars.	(i) l = 0	(ii) l = 1	(iii) l = 2	(iv) l = 0	(v) l = 1	(vi) l = 2
Intercept	-3.558 **	-3.172 **	-3.096 **	-33.386 **	-25.280 **	-35.963 **
	-5.10	*-6.40*	*-4.50*	*-8.19*	*-7.82*	*-10.11*
AVAL	0.342 **	0.307 **	0.302 **	1.581 **	1.200 **	1.286 **
	4.02	*4.77*	*3.62*	*6.26*	*5.10*	*5.69*
R&D	0.021	0.026	0.005	-0.408	0.152 *	-0.404
	0.82	*1.16*	*0.15*	*-1.86*	*2.56*	*-1.42*
dIH	0.000 *	0.000	0.000	-0.001	-0.002	0.002 **
	-2.55	*-1.02*	*0.53*	*-0.87*	*-1.11*	*7.66*
ROA	0.015 *	0.016 *	0.007	0.111 **	0.054 *	0.112 *
	2.56	*2.23*	*1.10*	*2.88*	*2.02*	*2.51*
RVOLA	0.236 **	0.157 **	0.130 **	1.142 **	-3.272 **	-1.056 **
	6.09	*5.51*	*3.81*	*3.56*	*-5.71*	*-3.27*
BTM	-0.231	-0.272 **	-0.124	-0.859	1.797 *	1.326 **
	-1.66	*-3.73*	*-1.30*	*-1.02*	*2.10*	*2.79*
NANA	-0.002	0.003	0.002	0.051	0.051	0.062 *
	-0.16	*0.19*	*0.15*	*1.54*	*1.51*	*2.37*
LDV	1.403	0.992	1.274	0.148	0.279	0.174
	1.09	*1.21*	*1.04*	*1.07*	*1.82*	*1.12*
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj-Rsqr	0.052	0.064	0.043	0.030	0.042	0.029
Obs	22,517	22,573	22,249	21,816	21,794	21,005

Table 8
With Ω_m or Π_e as the Dependent Variable

This table reports the results of pooled regressions with Ω_m (in Panel A) or Π_e (in Panel B) as the dependent variable using the firms that have positive values in the number of granted patents or in the number of patent citations. NYSE/AMEX-listed ordinary common stocks only (SHRCD = 10 or 11 in CRSP) are used over the 84 quarters (1990:Q1-2010:Q4). The dependent variables used in the two panels are defined as follows: Ω_m: the quarterly average of monthly values in $\omega^m = \lambda^{FV,m} * DOIMB^m$, where $\lambda^{FV,m}$ is the monthly price-impact parameter estimated using intradaily dollar order flows (in $million) within each month based on the Foster and Viswanathan (1993) model, and $DOIMB^m$ is the monthly dollar-value order imbalance (in $million) computed as the monthly aggregated buyer-initiated dollar volume (obtained by adding intradaily buyer-initiated dollar volume within each month) minus the monthly aggregated seller-initiated dollar volume (obtained by adding intradaily seller-initiated dollar volume within each month); Π_e: the logit-transform of π_e^Q [i.e., $\ln\left(\frac{\pi_e^Q}{1-\pi_e^Q}\right)$], where π_e^Q is the quarterly average of values in π_e^M, which is in turn the monthly average of daily values in π_e [$\pi_e = (1 - \pi_\emptyset)$ is the daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that an information event occurs on a given day]. To process order flows used in the above variables, intradaily trades and quotes from ISSM/TAQ are matched (to classify into a buyer- or seller-initiated category) based on the Lee and Ready (1991) algorithm up to December 2006 and on the Holden and Jacobsen (2014) algorithm from January 2007 to December 2010. The explanatory variables are defined as follows: *ANPAT*: the natural logarithm of one plus quarterly *adj-NPAT*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of patents granted to firms that are granted at least one patent in the class in the quarter is calculated; (ii) the focal firm's patent number in the class in the quarter is scaled by the average number calculated in step (i) to get the adjusted patent counts in that class; and (iii) all the adjusted patent counts are added across all classes in the quarter to obtain *adj-NPAT* for the firm]; *ANCITE*: the natural logarithm of one plus quarterly *adj-NCITE*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of subsequent citations received (up to 2010) by the patents granted to the firms in this class is calculated; (ii) the number of subsequent citations received (up to 2010) by the patent granted to the firm in the class in the quarter is scaled by the average number of citations calculated in step (i) to get the adjusted patent citations in the class; and (iii) all the adjusted patent citations are added across all classes in the quarter to obtain *adj-NCITE* for the firm]; and *LDV*: one-quarter lagged value of the dependent variable (Ω_m or Π_e). Other variables are defined in the previous tables. The letter *l* is the lead order in the dependent variable: *l* = 0, 1, and 2 mean that the dependent variable in the regressions is contemporaneous, led by a quarter, and led by two quarters, respectively. 'Yes' indicates that the 11 industry or 20 year dummy variables are included in the regressions. The values in the first row for each explanatory variable are the coefficients from the pooled regressions, and the values italicized in the second row of each variable are within-industry clustered-error-consistent *t*-statistics. All coefficients are multiplied by 10. *Adj-Rsqr* is the adjusted R-squared. *Obs* is the number of observations (firm-quarters) used in the pooled regressions. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

(Table 8: continued)

Pooled Regressions with Alternative Measures of Informed Trading (1990Q1-2010Q4)												
	Panel A: With Ω_m						Panel B: With Π_e					
Explanat. Vars.	(i) *l* = 0		(ii) *l* = 1		(iii) *l* = 2		(iv) *l* = 0		(v) *l* = 1		(vi) *l* = 2	
Intercept	-19.091	**	-16.324	**	-15.885	**	-8.252	**	-3.593		-12.718	**
	-5.54		*-4.20*		*-4.13*		*-11.35*		*-1.89*		*-6.57*	
ANPAT	12.229	**	12.053	**	11.751	**	2.036	**	1.681	**	1.828	**
	3.19		*3.72*		*2.94*		*7.10*		*6.57*		*7.87*	
R&D	0.322		0.501		0.094		-0.598	**	0.183		-0.314	**
	0.54		*1.05*		*0.13*		*-9.66*		*1.44*		*-3.28*	
dIH	-0.001	**	-0.002		0.000		0.001		-0.001		0.000	
	-2.98		*-1.34*		*0.08*		*0.74*		*-0.83*		*0.40*	
ROA	0.424	*	0.444	*	0.264		0.115	**	0.076	**	0.022	
	2.31		*2.39*		*1.53*		*7.55*		*5.87*		*1.11*	
RVOLA	4.644	**	3.114	**	2.564	**	0.881	**	-3.412	**	-1.902	**
	4.57		*3.18*		*3.19*		*4.55*		*-8.81*		*-6.10*	
BTM	-11.456	*	-11.850	**	-8.244	*	-2.876	**	0.943	**	0.619	
	-2.41		*-3.97*		*-2.41*		*-3.65*		*3.71*		*1.11*	
NANA	0.537	**	0.534	**	0.475	**	0.172	**	0.132	**	0.153	**
	3.55		*2.76*		*3.77*		*4.69*		*3.76*		*4.33*	
LDV	1.565		1.051		1.614		-0.085		0.140		-0.105	
	1.11		*1.21*		*1.07*		*-0.49*		*0.78*		*-0.65*	
Industry Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Adj-Rsqr	0.052		0.061		0.048		0.064		0.078		0.061	
Obs	21,865		22,039		21,969		21,172		21,260		20,726	

Table 9

The Effect of an Exogenous Shock (the 1998 Court Decision) on Patent News and Informed Trading

This table reports the results of pooled regressions that incorporate the effect of an exogenous policy change in the relation between innovations and informed trading. The policy change is related to the decision by the Federal Circuit Court on the case of State Street Bank vs. Signature Financial Group in 1998, which officially established the patentability of software and business methods and thus substantially enhanced the value of patentable inventions in the finance and software industries. Panels A and B use Ω and Π_g, respectively, as the dependent variable. The sample includes the firms that have positive values in the number of granted patents or of patent citations, and ordinary common stocks only (SHRCD = 10 or 11 in CRSP) are used for NYSE/AMEX firms over the 16 quarters (1997:Q1-2000:Q4). The dependent variables are defined as follows: Ω: the quarterly average of ω^M, which is the monthly average of daily values in $\omega^D = \lambda^{FV} * DOIMB^D$, where λ^{FV} is the monthly price-impact parameter estimated using intradaily dollar order flows (in $million) within the previous month (month *m-1*) based on the Foster and Viswanathan (1993) model, and $DOIMB^D$ is the daily dollar-value order imbalance (in $million) in the current month (month *m*) computed as the daily aggregated buyer-initiated dollar volume (obtained by adding intradaily buyer-initiated dollar volume within each day) minus the daily aggregated seller-initiated dollar volume (obtained by adding intradaily seller-initiated dollar volume within each day); Π_g: the logit-transform of π_g^Q [i.e., $\ln\left(\frac{\pi_g^Q}{1-\pi_g^Q}\right)$], where π_g^Q is the quarterly average of values in π_g^M, which is in turn the monthly average of daily values in π_g [π_g is the daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that a good-news information event occurs on a given day]. To process order flows used in the above variables, intradaily trades and quotes from ISSM/TAQ are matched (to classify into a buyer- or seller-initiated category) based on the Lee and Ready (1991) algorithm up to December 2006 and on the Holden and Jacobsen (2014) algorithm from January 2007 to December 2010. The explanatory variables are defined as follows. *ANPAT*: the natural logarithm of one plus quarterly *adj-NPAT*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of patents granted to firms that are granted at least one patent in the class in the quarter is calculated; (ii) the focal firm's patent number in the class in the quarter is scaled by the average number calculated in step (i) to get the adjusted patent counts in that class; and (iii) all the adjusted patent counts are added across all classes in the quarter to obtain *adj-NPAT* for the firm]; I_{Y99on}: an indicator variable that equals one if the year is equal to or later than 1999, and zero otherwise; $I_{affected}$: an indicator variable that equals one if a sample firm is in the financial industry or business equipment industry, and zero otherwise; $ANPAT*I_{Y99on}*I_{affected}$: an interaction among *ANPAT*, I_{Y99on}, and $I_{affected}$; $ANPAT*I_{Y99on}$: an interaction between *ANPAT* and I_{Y99on}; $ANPAT*I_{affected}$: an interaction between *ANPAT* and $I_{affected}$; and *LDV*: one-quarter lagged value of the dependent variable (Ω or Π_g). Other variables are defined in the previous tables. The letter *l* is the lead order in the dependent variable: *l* = 0, 1, and 2 mean that the dependent variable in the regressions is contemporaneous, led by a quarter, and led by two quarters, respectively. 'Yes' indicates that the 11 industry or 20 year dummy variables are included in the regressions. The values in the first row for each explanatory variable are the coefficients from the pooled regressions, and the values italicized in the second row of each variable are within-industry clustered-error-consistent *t*-statistics. All coefficients are multiplied by 10. *Adj-Rsqr* is the adjusted R-squared. *Obs* is the number of observations (firm-quarters) used in the pooled regressions. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

(Table 9: continued)

The Effect of an Exogenous Shock (the 1998 Court Decision on the Case of State Street Bank vs. Signature Financial Group)												
	Panel A: Dep. Var. = $\boldsymbol{\Omega}$						Panel B: Dep. Var. = $\boldsymbol{\Pi_g}$					
Explanat. Vars.	(i) *l* = 0		(ii) *l* = 1		(iii) *l* = 2		(iv) *l* = 0		(v) *l* = 1		(vi) *l* = 2	
Intercept	-0.450	**	-0.075		0.257	**	-19.173	**	-8.144	**	-12.446	**
	-2.84		*-0.60*		*3.16*		*-10.43*		*-5.22*		*-7.14*	
ANPAT*I_{Y99on}*$I_{affected}$	1.049	**	1.055	**	0.956	**	2.768	**	2.397	**	2.106	
	4.42		*5.43*		*5.48*		*2.65*		*3.17*		*1.44*	
ANPAT	0.391	**	0.400	**	0.355	**	2.880	**	3.239	**	2.898	**
	3.35		*3.47*		*3.97*		*4.25*		*4.55*		*2.67*	
ANPAT*I_{Y99on}	-0.102		-0.113		-0.163		-0.826		-1.173		-1.612	
	-0.84		*-1.02*		*-1.30*		*-0.86*		*-1.55*		*-1.09*	
ANPAT*$I_{affected}$	-0.004		-0.024		-0.068		-1.927	**	-2.738	**	-1.644	*
	-0.05		*-0.27*		*-0.75*		*-4.13*		*-7.31*		*-2.18*	
R&D	0.004		0.050	*	0.030		-0.300	**	0.631	**	0.302	
	0.21		*2.09*		*1.57*		*-3.29*		*2.82*		*1.80*	
dIH	0.000		0.000		0.000	**	-0.002	**	-0.001		0.002	**
	-1.27		*-0.80*		*2.67*		*-4.20*		*-1.71*		*13.60*	
ROA	0.027	**	0.016	**	0.004		0.137		0.144	*	0.140	*
	2.61		*3.39*		*0.89*		*1.27*		*2.01*		*2.48*	
RVOLA	0.220	**	0.033		-0.037	**	1.784	**	-4.376	**	-2.674	**
	3.33		*0.72*		*-2.80*		*3.53*		*-6.45*		*-4.93*	
BTM	-0.523	**	-0.351		-0.436	*	-11.023	**	-1.285		-2.468	*
	-2.70		*-1.88*		*-2.10*		*-5.18*		*-1.47*		*-2.01*	
NANA	0.030	*	0.020	**	0.017	**	0.372	**	0.383	**	0.415	**
	2.53		*4.07*		*11.46*		*5.45*		*5.27*		*5.94*	
LDV	6.603	**	7.150	**	7.481	**	0.050		0.324	**	0.060	
	10.44		*16.58*		*27.12*		*0.54*		*2.75*		*0.46*	
Industry-Year Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Adj-Rsqr	0.634		0.588		0.606		0.065		0.081		0.056	
Obs	5,044		5,020		4,928		5,015		5,015		4,914	

Table 10

Two-stage Least Squares Regressions with Instrumental Variables

This table reports the results of two-stage least squares (2SLS) regressions using two instrumental variables (IVs): *AGTime* is the average time taken from patent application to its approval (or grant), and *NPATym3* is the number of patents granted three years before. The two IVs are lagged by 12 quarters to satisfy the exclusiveness condition. In the first stage, the innovation measure, *ANPAT*, is regressed on the two IVs (*AGTime* and *NPATym3*) together with the control variables in order to obtain the fitted (or predicted) values of the innovation measure. The fitted variable are denoted by *Fitted_ANPAT*. In the second stage, we regress the informed trading variable (Ω or Π_g) on the fitted innovation measure (*Fitted_ANPAT*) and other control variables. The sample includes the firms that have positive values in the number of granted patents or of patent citations, and ordinary common stocks only (SHRCD = 10 or 11 in CRSP) are used for NYSE/AMEX firms over the 84 quarters (1990:Q1-2010:Q4). The dependent variables used in the two panels are defined as follows: Ω: the quarterly average of ω^M, which is the monthly average of daily values in $\omega^D = \lambda^{FV} * DOIMB^D$, where λ^{FV} is the monthly price-impact parameter estimated using intradaily dollar order flows (in $million) within the previous month (month *m-1*) based on the Foster and Viswanathan (1993) model, and $DOIMB^D$ is the daily dollar-value order imbalance (in $million) in the current month (month *m*) computed as the daily aggregated buyer-initiated dollar volume (obtained by adding intradaily buyer-initiated dollar volume within each day) minus the daily aggregated seller-initiated dollar volume (obtained by adding intradaily seller-initiated dollar volume within each day); Π_g: the logit-transform of π_g^Q [i.e., $\ln\left(\frac{\pi_g^Q}{1-\pi_g^Q}\right)$], where π_g^Q is the quarterly average of values in π_g^M, which is in turn the monthly average of daily values in π_g [π_g is the daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that a good-news information event occurs on a given day]. To process order flows used in the above variables, intradaily trades and quotes from ISSM/TAQ are matched (to classify into a buyer- or seller-initiated category) based on the Lee and Ready (1991) algorithm up to December 2006 and on the Holden and Jacobsen (2014) algorithm from January 2007 to December 2010. Other variables are defined in the previous tables. The letter *l* is the lead order in the dependent variable: *l* = 0, 1, and 2 mean that the dependent variable in the regressions is contemporaneous, led by a quarter, and led by two quarters, respectively. 'Yes' indicates that the 11 industry or 20 year dummy variables are included in the regressions. The values in the first row for each explanatory variable are the coefficients from the pooled regressions, and the values italicized in the second row of each variable are within-industry clustered-error-consistent *t*-statistics. All coefficients are multiplied by 10. *Centered-Rsqr* is the centered R-squared. *Obs* is the number of observations (firm-quarters) used in the regressions. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively. In the lower part in each panel, the Kleibergen-Paap *rk LM*-statistic (*Kleibergen-Paap Stat*) for an under-identification test (and *p*-values in italic) and Hansen *J*-statistic (*Hansen J Stat*) for an over-identification test (and *p*-values in italic) are reported. The null hypothesis for the under-identification test is "the IVs cannot explain endogenous explanatory variables," and the rejection of the null hypothesis indicates that the IVs can significantly explain the endogenous variable (and thus are relevant). The null hypothesis for the over-identification test is "H_0: The IVs are uncorrelated with the errors from the original regression," and the rejection of the null hypothesis indicates that the IVs are invalid.

(Table 10: continued)

	2SLS Regressions with Two Instrumental Variables											
	Panel A: Dep. Var. = $\boldsymbol{\Omega}$						Panel B: Dep. Var. = $\boldsymbol{\Pi_g}$					
Explanat. Vars.	(i) *l* = 0		(ii) *l* = 1		(iii) *l* = 2		(iv) *l* = 0		(v) *l* = 1		(vi) *l* = 2	
Intercept	-1.160	**	-0.792	**	-0.552	*	-19.338	**	-10.969	**	-18.841	**
	-4.98		*-3.34*		*-2.56*		*-8.16*		*-4.39*		*-5.46*	
Fitted_ANPAT	1.001	**	0.976	**	0.952	**	1.545	**	1.279	**	1.268	**
	4.67		*4.60*		*4.56*		*4.12*		*3.70*		*3.75*	
R&D	0.023		0.058	**	0.042	**	-0.663	*	0.080		-0.152	
	0.94		*3.29*		*2.58*		*-1.97*		*0.59*		*-0.81*	
dIH	0.000		0.000		0.000		-0.001		-0.001		0.003	**
	-0.20		*-0.28*		*0.26*		*-0.61*		*-0.54*		*5.24*	
ROA	0.043	**	0.051	**	0.035	**	0.277	*	0.111		-0.015	
	4.91		*4.05*		*2.89*		*2.50*		*1.45*		*-0.20*	
RVOLA	0.299	**	0.230	**	0.181	**	0.959	**	-2.968	**	-1.429	**
	5.95		*4.27*		*4.15*		*4.16*		*-8.59*		*-4.39*	
BTM	-0.760	**	-0.607	**	-0.553	**	-3.771	**	-1.097		-1.880	
	-4.85		*-4.11*		*-4.26*		*-2.71*		*-0.71*		*-1.17*	
NANA	0.009		0.006		0.006		0.167	**	0.154	**	0.185	**
	0.52		*0.35*		*0.31*		*4.45*		*4.21*		*4.95*	
LDV	1.438		1.454		1.430		0.432	**	0.495	**	0.408	**
	1.23		*1.23*		*1.22*		*4.58*		*5.16*		*3.97*	
Industry Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Centered-Rsqr	0.068		0.066		0.064		0.034		0.040		0.030	
Obs	16,654		16,200		15,725		16,076		15,706		14,918	
Kleibergen-Paap Stat	858.93		875.86		855.40		886.22		938.55		961.04	
p-value	*0.00*		*0.00*		*0.00*		*0.00*		*0.00*		*0.00*	
Hansen J Stat	0.24		0.03		0.21		0.35		2.29		0.69	
p-value	*0.62*		*0.86*		*0.65*		*0.56*		*0.13*		*0.41*	

Table 11
Who is Active in Trading on Patent News?

This table reports the subsample analysis results (pooled regressions) to examine who is active in trading on patent-related information. NYSE/AMEX-listed ordinary common stocks only (SHRCD = 10 or 11 in CRSP) are used over the 84 quarters (1990:Q1-2010:Q4). In each quarter, the component firms are sorted on the average of changes in short-term institutional ownership (*dSIO*) to construct four equal-sized portfolios, and the pooled regression results are reported for the top (*High* group) and bottom (*Low* group) quartiles in Panel A. For each firm in each quarter, the correlation between the change in *ANPAT* (denoted by *dANPAT*) and *dSIO* over the eight quarters in the past (quarters *q-1* to *q-8*) is computed, and the component firms are sorted on this correlation, and then the pooled regression results are reported for the top (*High* group) and bottom (*Low* group) quartiles in Panel B. The dependent variables used are defined as follows: Ω: the quarterly average of ω^M, which is the monthly average of daily values in $\omega^D = \lambda^{FV} * DOIMB^D$, where λ^{FV} is the monthly price-impact parameter estimated using intradaily dollar order flows (in $million) within the previous month (month *m-1*) based on the Foster and Viswanathan (1993) model, and $DOIMB^D$ is the daily dollar-value order imbalance (in $million) in the current month (month *m*) computed as the daily aggregated buyer-initiated dollar volume (obtained by adding intradaily buyer-initiated dollar volume within each day) minus the daily aggregated seller-initiated dollar volume (obtained by adding intradaily seller-initiated dollar volume within each day); Π_g: the logit-transform of π_g^Q [i.e., $\ln\left(\frac{\pi_g^Q}{1-\pi_g^Q}\right)$], where π_g^Q is the quarterly average of values in π_g^M, which is in turn the monthly average of daily values in π_g [π_g is the daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that a good-news information event occurs on a given day]. To process order flows used in the above variables, intradaily trades and quotes from ISSM/TAQ are matched (to classify into a buyer- or seller-initiated category) based on the Lee and Ready (1991) algorithm up to December 2006 and on the Holden and Jacobsen (2014) algorithm from January 2007 to December 2010. The explanatory variables are defined as follows: *ANPAT*: the natural logarithm of one plus quarterly *adj-NPAT*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of patents granted to firms that are granted at least one patent in the class in the quarter is calculated; (ii) the focal firm's patent number in the class in the quarter is scaled by the average number calculated in step (i) to get the adjusted patent counts in that class; and (iii) all the adjusted patent counts are added across all classes in the quarter to obtain *adj-NPAT* for the firm]; *dANPAT*: the change in *ANPAT*; and *LDV*: one-quarter lagged value of the dependent variable (Ω or Π_g). Other variables are defined in the previous tables. The letter *l* is the lead order in the dependent variable: *l* = 0 means that the dependent variable in the regressions is contemporaneous. 'Yes' indicates that the 11 industry or 20 year dummy variables are included in the regressions. The values in the first row for each explanatory variable are the coefficients from the pooled regressions, and the values italicized in the second row of each variable are within-industry clustered-error-consistent *t*-statistics. All coefficients are multiplied by 10. The Chi-square statistic to test if the difference in the coefficients on *ANPAT* for the *High* and *Low* quartiles (*High* - *Low*) is zero is reported in bracket. *Adj-Rsqr* is the adjusted R-squared. *Obs* is the number of observations (firm-quarters) used in the pooled regressions. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

(Table 11: continued)

	Panel A: With the Changes in Short-term Institutional Holdings (*dSIO*)				Panel B: With the Correlation between *dANPAT* and *dSIO* in the Past			
	Dep. Var. = $\boldsymbol{\Omega}$, *l* = 0		Dep. Var. = $\boldsymbol{\Pi_g}$, *l* = 0		Dep. Var. = $\boldsymbol{\Omega}$, *l* = 0		Dep. Var. = $\boldsymbol{\Pi_g}$, *l* = 0	
Explanat. Vars.	High	Low	High	Low	High	Low	High	Low
Intercept	-0.499	-0.569 **	-21.405 **	-16.924 **	-1.152 **	-0.901 **	-18.865 **	-9.859 **
	-1.09	*-6.05*	*-9.92*	*-11.26*	*-3.43*	*-7.61*	*-3.47*	*-4.79*
ANPAT	0.550 **	0.033	2.933 **	0.948	0.534 **	0.191	1.916 **	1.376
	2.71	*1.83*	*6.23*	*1.58*	*6.55*	*1.88*	*6.35*	*1.84*
R&D	0.020	-0.014	-0.841	-0.765	0.160	0.034	0.178	-0.420
	0.62	*-1.63*	*-1.32*	*-1.07*	*0.56*	*0.48*	*0.62*	*-0.93*
dIH	0.001	0.001 *	0.075 **	-0.023 **	0.001	0.000 **	0.012	0.017
	0.48	*2.40*	*3.11*	*-4.26*	*0.76*	*-3.00*	*0.37*	*1.73*
ROA	0.021 **	0.003	0.187	0.118 **	0.048 *	0.009 *	0.247	0.040
	5.99	*1.55*	*1.46*	*3.37*	*2.25*	*2.20*	*0.89*	*0.39*
RVOLA	0.206 **	0.087 **	1.648 **	1.398 **	0.354 **	0.131 **	0.968	0.184
	4.24	*3.37*	*5.00*	*3.43*	*4.32*	*4.69*	*1.70*	*0.34*
BTM	0.012	-0.146 **	-4.879 **	-3.421	-0.704 **	-0.306 **	-3.971	-0.672
	0.05	*-2.62*	*-3.42*	*-1.93*	*-4.21*	*-5.03*	*-1.28*	*-0.40*
NANA	0.032 **	0.015 **	0.153	0.358 **	0.053 **	0.026 **	0.105	0.232 **
	5.04	*7.24*	*1.25*	*5.74*	*3.20*	*6.71*	*1.43*	*2.83*
LDV	1.348	6.035 **	0.045	-0.003	0.700	4.956 **	0.294	0.342
	1.64	*11.85*	*1.39*	*-0.03*	*0.89*	*8.05*	*1.71*	*1.90*
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-Rsqr	0.008	0.614	0.029	0.019	0.216	0.283	0.037	0.028
Obs	4,853	4,803	4,725	4,708	4,595	4,540	4,456	4,388
(High - Low)	0.517*	*[6.24]*	1.985**	*[13.55]*	0.343*	*[6.62]*	0.540*	*[4.84]*

Table 12

Cross-Firm Effects of Patent News on Informed Trading in Rival Firms

This table reports the results of pooled regressions using the rival firms which obtain no patent/citation or relatively a smaller number of patents/citations in a quarter, compared to their competitor (a "focal" firm) which obtains a larger number of patents/citations. Panels C and D report the results of pooled regressions using both the focal firms and their matched rival firms. For a focal firm which obtains patents/citations in each quarter, its rival firms are matched based on the product similarity scores (available from 1996) computed by Hoberg and Phillips (HP) (2010, 2016). Since the HP score is calculated on an annual basis, the score is assumed to be constant over the four quarters within a year. For a matched pair (focal firm *i* and rival firm *j*), *Ratio_NPAT* = ($adj\text{-}NPAT_j$ – $adj\text{-}NPAT_i$)/($adj\text{-}NPAT_j$ + $adj\text{-}NPAT_i$) and *Ratio_NCITE* = ($adj\text{-}NCITE_j$ – $adj\text{-}NCITE_i$)/($adj\text{-}NCITE_j$ + $adj\text{-}NCITE_i$) are computed each quarter, and then for a focal firm the nearest three rival firms are selected (based on the HP score) after restricting that each of the two ratios (*Ratio_NPAT*, *Ratio_NCITE*) is equal to or smaller than -0.8. NYSE/AMEX-listed ordinary common stocks only (SHRCD = 10 or 11 in CRSP) are used over the 64 quarters (1996:Q1-2010:Q4). The pooled regression results from using the matched rival firms are contained in Panels A and B. Both focal firms and their matched rival firms are included for regressions in Panels C and D, where Π_b is used as the dependent variable together with a dummy variable for the rival firms (I_{rival}). The dependent variables used in the four panels are defined as follows. Ω: the quarterly average of ω^M, which is the monthly average of daily values in $\omega^D = \lambda^{FV} * DOIMB^D$, where λ^{FV} is the monthly price-impact parameter estimated within the previous month (month *m-1*) based on the Foster and Viswanathan (1993) model, and $DOIMB^D$ is the daily dollar-value order imbalance (in $million) in the current month (month *m*) computed as the daily aggregated buyer-initiated dollar volume minus the daily aggregated seller-initiated dollar volume; Π_g: the logit-transform of π_g^Q [i.e., $\ln\left(\frac{\pi_g^Q}{1-\pi_g^Q}\right)$], where π_g^Q is the quarterly average of values in π_g^M, which is in turn the monthly average of daily values in π_g (which defined in the previous tables); Π_b: the logit-transform of π_b^Q [i.e., $\ln\left(\frac{\pi_b^Q}{1-\pi_b^Q}\right)$], where π_b^Q is the quarterly average of values in π_b^M, which is in turn the monthly average of daily values in π_b [which is the daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that a bad-news information event occurs on a given day]. To process order flows used in the above variables, intradaily trades and quotes from ISSM/TAQ are matched based on the Lee and Ready (1991) algorithm up to December 2006 and on the Holden and Jacobsen (2014) algorithm from January 2007 to December 2010. The explanatory variables are defined as follows: *ANPAT*: the natural logarithm of one plus quarterly *adj-NPAT*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of patents granted to firms that are granted at least one patent in the class in the quarter is calculated; (ii) the focal firm's patent number in the class in the quarter is scaled by the average number calculated in step (i) to get the adjusted patent counts in that class; and (iii) all the adjusted patent counts are added across all classes in the quarter to obtain *adj-NPAT* for the firm]; *NCITE*: the quarterly (unadjusted) number of patent citations received within the following three years; *ANCITE*: the natural logarithm of one plus quarterly *adj-NCITE*, which is computed in three steps [i.e., (i) for each technology class in each quarter, the average number of subsequent citations received (up to 2010) by the patents granted to the firms in this class is calculated; (ii) the number of subsequent citations received (up to 2010) by the patent granted to the firm in the class in the quarter is scaled by the average number of citations calculated in step (i) to get the adjusted patent citations in the class; and (iii) all the adjusted patent citations are added across all classes in the quarter to obtain *adj-NCITE* for the firm]; I_{rival}: an indicator variable that equals one if an observation is a rival firm and zero if it is a focal firm; $ANPAT*I_{rival}$: an interaction between *ANPAT* and I_{rival}; and *LDV*: one-quarter lagged value of the dependent variable (Ω, Π_g, or Π_b). Other variables are defines in the previous tables. All coefficients are multiplied by 10. *Adj-Rsqr* is the adjusted R-squared. *Obs* is the number of observations (firm-quarters) used in the pooled regressions. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

(Table 12: continued)

Informed Trading in Rival Firms (1996Q1-2010Q4)												
	Panel A: Dep. Var. = $\boldsymbol{\Omega}$						Panel B: Dep. Var. = $\boldsymbol{\Pi_g}$					
Explanat. Vars.	(i) l = 0		(ii) l = 1		(iii) l = 2		(iv) l = 0		(v) l = 1		(vi) l = 2	
Intercept	-0.295	*	0.001		0.053		-21.274	**	-15.376	**	-21.698	**
	-1.96		*0.06*		*1.61*		*-11.79*		*-8.76*		*-10.72*	
ANPAT	0.059		0.000		-0.004		0.721		1.676		1.089	
	0.81		*0.00*		*-0.08*		*0.77*		*1.68*		*1.37*	
R&D	0.001		0.008	*	-0.007		0.142		0.079		-0.001	
	0.12		*2.43*		*-0.50*		*0.88*		*0.56*		*-0.01*	
dIH	0.001		0.001		0.000		0.071		-0.039		0.080	
	0.79		*1.04*		*-0.12*		*1.69*		*-0.71*		*1.32*	
ROA	0.013	*	0.004	**	-0.004		0.218	*	0.064	*	0.127	
	2.21		*2.76*		*-0.46*		*2.09*		*2.05*		*1.73*	
RVOLA	0.042	*	-0.016		-0.005		-0.310		-2.544	**	-1.299	**
	2.32		*-1.37*		*-0.35*		*-1.24*		*-5.28*		*-2.72*	
BTM	-0.067		-0.016		-0.059		-1.109	*	-0.283		-0.827	
	-1.23		*-0.52*		*-1.14*		*-2.13*		*-1.11*		*-1.88*	
NANA	0.028	**	0.014	**	0.014	**	0.608	**	0.512	**	0.534	**
	2.84		*3.17*		*3.05*		*7.92*		*7.84*		*8.48*	
LDV	3.872	**	6.284	**	6.295	**	0.293	**	0.316	**	0.237	*
	2.66		*13.26*		*13.71*		*2.91*		*3.16*		*2.30*	
Industry Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Adj-Rsqr	0.105		0.158		0.147		0.044		0.057		0.046	
Obs	26,425		25,975		25,624		25,574		25,502		24,701	

(Table 12: continued)

Cross-Firm Effects (1996Q1-2010Q4): Dep. Var. = Π_b with a Rival Dummy Variable													
Panel C: With *ANPAT*							Panel D: With *ANCITE*						
Explanat. Vars.	(i) *l* = 0		(ii) *l* = 1		(iii) *l* = 2		Explanat. Vars.	(iv) *l* = 0		(v) *l* = 1		(vi) *l* = 2	
Intercept	-19.725	**	-10.546	**	-21.468	**	Intercept	-14.771	**	-7.548		-28.053	*
	-7.42		*-3.23*		*-5.44*			*-7.41*		*-1.21*		*-2.04*	
ANPAT	0.825		-0.123		-0.013		ANCITE	-0.134		-0.230		-0.138	
	0.85		*-0.18*		*-0.02*			*-0.42*		*-0.81*		*-0.50*	
I_{rival}	0.152		-1.703		-2.248		I_{rival}	-3.922		-2.414		-2.798	
	0.08		*-1.24*		*-1.54*			*-1.08*		*-1.59*		*-1.59*	
ANPAT*I_{rival}	5.396	**	-1.631		1.741		ANCITE*I_{rival}	2.419	**	-0.099		0.601	
	3.01		*-0.50*		*0.52*			*3.76*		*-0.22*		*0.78*	
R&D	-1.290		-1.488	*	-1.906	**	R&D	-2.832	*	-2.502	**	-2.127	**
	-1.63		*-1.96*		*-3.10*			*-2.05*		*-3.04*		*-3.02*	
dIH	0.017		-0.012		-0.003		dIH	0.017		-0.013		-0.002	
	0.70		*-0.72*		*-0.52*			*0.70*		*-0.71*		*-0.40*	
ROA	0.188	**	-0.113		-0.092		ROA	0.203	**	-0.180	**	-0.080	
	3.31		*-1.07*		*-0.55*			*2.58*		*-2.58*		*-0.57*	
RVOLA	-1.163	**	-7.008	**	-4.183	**	RVOLA	-2.219	*	-8.469	**	-5.135	**
	-2.98		*-5.62*		*-3.09*			*-2.52*		*-11.31*		*-4.48*	
BTM	-3.073	**	-0.716		-1.589		BTM	-2.391	**	-0.304		-0.818	
	-6.04		*-0.85*		*-1.32*			*-3.08*		*-0.36*		*-0.71*	
NANA	0.234	**	0.213	*	0.237	*	NANA	0.201	*	0.160		0.196	*
	3.03		*1.98*		*2.38*			*2.56*		*1.61*		*2.01*	
LDV	0.671	**	0.753	**	0.765	**	LDV	0.653	**	0.652	**	0.700	**
	8.01		*7.36*		*6.71*			*7.00*		*6.80*		*6.54*	
Industry Fixed Effects	Yes		Yes		Yes		Industry Fixed Effects	Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes		Year Fixed Effects	Yes		Yes		Yes	
Adj-Rsqr	0.072		0.079		0.073		Adj-Rsqr	0.073		0.082		0.074	
Obs	38,952		39,003		37,783		Obs	38,146		38,069		36,967	