April 29, 2018

Technology Competition and Informed Trading: Evidence from Weekly Patent Announcements

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We are grateful for the insightful comments provided by two anonymous referees and the editor, Itay Goldstein. We thank Gerard Hoberg for providing the data on the product similarity scores [used in Hoberg and Phillips (2010, 2016)]; Craig Holden for the SAS code on the Holden-Jacobsen (2014) algorithm; and Rui Albuquerque, Matthew Billett, Michael Brennan, Tarun Chordia, Carole Comerton-Forde, Vyacheslav Fos, Avanidhar Subrahmanyam, Sheridan Titman, and Rossen Valkanov for their valuable discussions and feedback. Research assistance was ably provided by Seung-Oh Han, Jung-Eun Ustina Huh, Jung-Hyun Deborah Huh, and Rachel Ma. All errors are solely the authors' responsibility.

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Abstract

By constructing weekly measures of informed trading and technology competition, we provide evidence that news about a firm's relative disadvantage in technology competition leads to informed selling in financial markets. A causal interpretation of our results is supported by two-stage least squares regressions that use an instrumental variable devised based on the citations inserted by patent examiners. A firm's unfavorable status in competition predicts lower subsequent stock returns, and informed trading on such news is profitable. In particular, institutional investors actively assess the status of firms' technology competition and capitalize on their informational advantage through trading activities, achieving higher returns.

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

***Keywords*:** Information Asymmetry; Informed Trading; Conditional Probability of Informed Trading; Corporate Innovation; Patenting Activities; Product Similarity Scores; Technology Competition; Relative Disadvantage

1. Introduction

The theoretical models of Kim and Verrecchia (1994, 1997) and Kandel and Pearson (1995) suggest that different agents have different interpretations of public information signals or different abilities to process information from public announcements. Innovating activities may result in information asymmetry in a firm, providing an opportunity for some investors to take advantage of their informational advantage, which in turn leads to trading activities in financial markets (Chordia, Huh, and Subrahmanyam, 2007; Engelberg, Reed, and Ringgenberg, 2012). Indeed, Krinsky and Lee (1996), Green (2004), and Brennan, Huh, and Subrahmanyam (2018) provide evidence that informed trading occurs even *after* the announcements of various corporate events (e.g., M&As, SEOs, dividend initiations, and earnings announcements), which make related information *public*.[1]

Most corporate finance studies focus on the effects of a firm's corporate events on its firm value or other important variables in the absolute sense, without considering the firm's comparative (dis)advantage that similar events occurring in its rival firms may cause. For example, if Apple Inc. has recently developed useful technology for its cell phones, we may consider it good news for Apple. However, if its rival firm, Samsung Electronics Co., has developed better technology for its own products around the same time, Apple may be at a relative disadvantage, which is rather bad news for Apple. Therefore, it is important to evaluate the effects of any corporate event from a relative perspective. However, there are very few studies that examine how rivals' corporate events affect the value or trading activities of (focal) firms. In today's business environments under which technology competition is fierce, the survival of a firm is not

[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).

only determined by its own innovating activities but also by competition from its rivals.[2]

In this study, we examine whether news related to technology competition a firm faces leads to informed trading in shares of the firm. For this purpose, we obtain patent-related data from the U.S. Patent and Trademark Office (USPTO), which 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") analyze the details of the new patent-related information and interpret its implications. This is because most of them do not have adequate expertise or resources to collect and process information about the new intellectual property on a daily or weekly basis. Investors with knowledge, experience, and resources in assessing patent announcements thus have informational advantages over the rest of the general public, which may lead to informed trading.

To examine the impact of technology competition on informed trading at a weekly frequency, we estimate a high-frequency measure of informed trading developed by Brennan, Huh, and Subrahmanyam (2018). Specifically, we employ the conditional probability of informed trading on bad news (denoted as Π_b) on a weekly basis. This measure is not subject to common limitations mentioned in the market microstructure literature. First, traditional measures, such as *PIN*, cannot distinguish informed trading on bad news from informed trading on good news. Moreover, as Brennan, Huh, and Subrahmanyam (2016) point out, another significant limitation of *PIN* is a long estimation window and hence low frequency (often annual), which makes it fail to reflect time-varying features in informed trading around event dates. Therefore, we compute the informed-trading measure at a weekly frequency to ensure that it can effectively capture trading activities around the weekly patent announcements.

[2] See Lerner (1995) and Hall (2004).

Our objectives in this study are threefold. First, by constructing relevant measures of informed trading and technology competition, we test whether in practice some investors track competition-related patent news released on Tuesday and trade based on such information. Second, if some market participants do react to such news, we investigate whether a firm's weaker competitive edge in technology can predict its subsequent stock returns, providing an opportunity to profit from informed trading. Third, we attempt to identify specifically who are more active in informed trading on the unfavorable news about technology competition and whether they can make profits from such trading.

Given the patent news publicly announced by the USPTO, it is very plausible that some market participants look for data on patenting activities, produce useful information, interpret the implications of such information for future cash flows in focal and rival firms, and eventually reveal the information through trading activities in shares of these firms. In fact, there are many forums and blogs that track the weekly *Official Gazette* and discuss the strengths and weaknesses of newly granted patents.[3]

We combine and extend the updated NBER patent data, the dataset organized by Kogan, Papanikolaou, Seru, and Stoffman (2017), and the Harvard Business School patent inventor data (Li et al., 2014) to construct a proxy for firm-level technology competition at a weekly frequency. Specifically, we identify a (focal) firm's 10 nearest rivals based on the product similarity scores computed by Hoberg and Phillips (2010, 2016) (HP-scores). Then the measure of technology competition of the firm is defined as the difference between the HP-score-weighted average number of new citations received by its rivals minus the number of new citations received by the firm itself (as of Tuesday). As the HP-scores are available since 1996, our sample starts from January 1996 and ends in December 2013 for all NYSE/AMEX- and NASDAQ-listed firms. In addition to the above citation-based measure (denoted as C_{rmf}), we also consider an alternative measure for technology

[3]For instance, see: http://www.patentlymobile.com/

competition, which is defined as the difference between the HP-score-weighted average number of new patents granted to its rivals minus the number of new patents granted to the firm itself (denoted as P_{rmf}).

When a patent receives more citations, it is more pertinent to the novelty, non-obviousness, and usefulness of subsequent patentable inventions; it is thus considered as more relevant to the current status of technological innovation.[4] Prior studies also show that the number of citations received by a patent is positively related to its probability of winning innovation awards (Carpenter, Narin, and Woolf, 1981), leading to new drugs (Narin, Noma, and Perry, 1987), peers' evaluation (Albert, Avery, Narin, and McAllister, 1991), and being licensed (Sampat and Ziedonis, 2005). In addition, studies provide evidence on the positive effect of firm-level citations on accounting profitability (Gu, 2005; Matolcsy and Wyatt, 2008; Pandit, Wasley, and Zach, 2011). All of these discussions justify our use of the citation-based proxy (C_{rmf}) as the primary measure of technology competition, instead of the patent count-based proxy (P_{rmf}), for our analyses.

We first examine whether keener technology competition a firm faces causes informed trading at a weekly frequency. In doing so, we use the measure of informed selling (Π_b) computed over three trading days (Tuesday-Thursday) in each week, because Kogan et al. (2017) document that the majority of price reactions to patent announcements occur within the three-day window. Our results show that a firm facing stiffer technology competition from its rival firms (i.e., a firm being at a greater disadvantage over its rivals) indeed experiences more informed trading (selling) on the bad news during the week. On the other hand, we find much weaker relations between the patent count-based measure of technology competition and the informed-trading measure, suggesting that

[4] The use of citations for technological importance can be traced back to Price (1963) and Trajtenberg (1990). The Office of Technology Assessment and Forecast (1976) states, "if a single document is cited in numerous patents, the technology revealed in that document is apparently involved in many developmental efforts. Thus, the number of times a patent document is cited may be a measure of its technological significance." Jaffe, Trajtenberg, and Fogarty (2000) and Hall, Jaffe, and Trajtenberg (2005a, 2005b) all support using the number of citations to measure technological importance.

the citation-based proxy better reflects the quality of patents. When we separate the competition measure into two elements (citations received by the focal firm and those received by its rival firms), we find consistent results. This corroborates that evaluating the performance of innovating activities from a relative perspective is important.

Our results are little affected by controlling for R&D intensity, changes in insider holdings, and other variables that are known to explain information asymmetry, as well as the firm and year-week fixed effects in the panel regressions. The results are also robust when we use five rivals, exclude self-citations or citations received by expired patents, and include citations made by patent applicants only. The above findings altogether support the hypothesis that the patent-related news reflecting a firm's competitive edge is an important determinant and predictor of informed trading in financial markets.

We note the possibility that our empirical results are vulnerable to endogeneity. To address this issue, we conduct two-stage least squares (2SLS) regressions by devising an instrumental variable: a competition proxy constructed based on the citations added by patent examiners. The idea is that the citations added by examiners are related only to technology relevance, and not to any other non-technological aspect of the patent or the firm. In the first stage, we find that the instrumental variable is highly positively correlated with the competition measure constructed based on the citations made by patent applicants. The second-stage estimation results show that the competition measure fitted in the first-stage regression is positively and significantly associated with the informed-selling measure, which confirms the causal relations between firm-level patent news and informed trading, ruling out the influence of omitted variables.

Next, we turn to the return predictability of technology competition. We find that the competition measure (computed as of Tuesday) is strongly negatively associated with the announcement return computed over the Tuesday-Thursday period, demonstrating that fiercer technology competition from rival firms predicts lower subsequent stock returns in a firm. This in turn suggests that informed investors can profit from trading on the bad news related to a firm's technology competition. Therefore, trading activities of informed traders are the channel through which the information about technology competition is impounded in stock prices.

Finally, we examine specifically who actively evaluates the news about technology competition and trades on such information. For this, we utilize the ANcerno database. Our empirical tests show that the stiffer the technology competition is for a firm, the higher the level of institutional investors' net selling of the firm's shares in that week. That is, institutional investors react to the bad news about a firm's competitive edge by selling shares of the firm. Furthermore, institutional investors are able to achieve higher returns from this trading strategy. Overall, our analyses support the notion that some institutional investors are informed traders who actively assess a firm's status in technology competition and capitalize on their information advantage through trading.

Previous studies document that innovating activities and resultant intellectual property play an important role in improving firm value (Scherer, 1965; Griliches, 1981; Hall, 1993). More recent studies also provide abundant evidence on the positive effect of firm-level innovating activities on subsequent stock returns (Cohen, Diether, and Malloy, 2013; Hirshleifer, Hsu, and Li, 2013, 2017). By contrast, little is known about how news about patenting activities is reflected in stock prices. So far as we are aware, this study is the first research that focuses on the *channel* (i.e., trading) through which information about relative disadvantage in competition measured by patent citations is impounded in stock prices, using a high-frequency measure of informed trading for a broad (NYSE/AMEX/NASDAQ) and long (18 years, 921 weeks) sample of firms.

This study also adds to the finance literature by highlighting the role of competition in corporate innovation. Prior studies on innovation and asset pricing [e.g., Lin (2012), Kogan et al. (2017), Cohen, Diether, and Malloy (2013), and Hirshleifer, Hsu, and Li

(2013)] focus on the positive effect of individual firms' technological development in the absolute sense. However, few researchers study the implications of intense technology competition for stock prices and firm value. In this paper, we provide novel evidence that news about *relative* disadvantage in technology competition has a negative impact on subsequent stock returns and firm value.

2. Variable Construction and Data

2.1. The Measures of Informed Trading

Since this study examines the effects of technology competition on informed trading on a weekly basis, we need high-frequency measures of informed trading. The vast majority of prior studies estimate informed trading measures, such as *PIN*, at a low (mostly annual) frequency using long windows of daily data (e.g., Easley, Hvidkjaer, and O'Hara, 2002; Mohanram and Rajgopal, 2009; Duarte and Young, 2009; Lai, Ng, and Zhang, 2014). However, these long estimation windows and low frequency limit the precision and reliability of the conclusions, particularly when the focus is on trading around corporate events, since informed trading is likely to be concentrated on only a few days around the announcement dates. Moreover, the existing measures of informed trading cannot distinguish the direction of trading.

Following Brennan, Huh, and Subrahmanyam (2018), therefore, we construct high-frequency (daily) measures of informed trading, which allow us to characterize more precisely the behavior of informed traders in several ways. First, we distinguish between informed selling and informed buying, as in Brennan, Huh, and Subrahmanyam (2016). By doing so, we can relate the direction of informed trading to subsequent favorable or unfavorable corporate news. Second, by calculating the posterior probabilities of informed buying and selling each day, we can investigate the dynamics of informed trading around public announcements on a daily or weekly basis. Third, by conditioning on additional information (daily buys and sells), our measures can improve the precision of detecting informed-trading activities. While many previous studies have used estimates of *PIN*, they have relied almost exclusively on unconditional estimates.

2.1.1. π_b^w and Π_b Constructed Using the Daily Conditional Probabilities of Informed Selling

In the Easley, Kiefer, O'Hara, and Paperman (EKOP) (1996) model, one of three possible events occurs each day: no news (ϕ), good news (g), or bad news (b). The unconditional probabilities of these events are given by $Pr(\phi) = (1 - \alpha)$, $Pr(g) = \alpha(1 - \delta)$, and $Pr(b) = \alpha\delta$, respectively, where α is the probability that an information event occurs on the day, and δ is the probability that the event is bad news. If an event occurs, it is observed only by informed traders who trade to take advantage of it: 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, noise traders buy and sell at the rates ϵ_B and ϵ_S, respectively. The authors show how to estimate the model parameters from a time series of the numbers of daily buyer- and seller-initiated transactions. The unconditional probability of informed trading, *PIN*, is defined as the probability that a trade is initiated by an informed trader.

Following Brennan, Huh, and Subrahmanyam (2018), we construct the posterior probability that a given 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) that day. Using Bayes' rule, the daily posterior probability that no information event has occurred on a given day, conditional on observing B and S, can be written as:

$$Pr(\phi|B,S) = \frac{Pr(B,S|\phi)Pr(\phi)}{Pr(B,S|\phi)Pr(\phi) + Pr(B,S|g)Pr(g) + Pr(B,S|b)Pr(b)}. \qquad (1)$$

Similar expressions can be derived for the posterior probabilities that good-news and bad-news events have occurred: $Pr(g|B,S)$ and $Pr(b|B,S)$, respectively.

Given the five parameters (α, δ, μ, ϵ_B, and ϵ_S) estimated in each month, it follows from the analysis of Easley et al. (1996) that the daily posterior probabilities are given by:

$$\pi(\phi|B,S) \equiv Pr(\phi|B,S) = \frac{(\alpha-1)e^{\mu}\epsilon_B^B\epsilon_S^S}{\alpha(\delta-1)\epsilon_S^S(\epsilon_B+\mu)^B - \epsilon_B^B[\alpha\delta(\epsilon_S+\mu)^S + (1-\alpha)e^{\mu}\epsilon_S^S]} \quad (2)$$

$$\pi(g|B,S) \equiv Pr(g|B,S) = \frac{\alpha(\delta-1)\epsilon_S^S(\epsilon_B+\mu)^B}{\alpha(\delta-1)\epsilon_S^S(\epsilon_B+\mu)^B - \epsilon_B^B[\alpha\delta(\epsilon_S+\mu)^S + (1-\alpha)e^{\mu}\epsilon_S^S]} \quad (3)$$

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

We denote the above posterior probabilities calculated each day by 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 $\pi_e = (1-\pi_\phi)$. We term π_b (π_g) as the posterior probability of informed trading on bad (good) news, or the posterior probability of informed selling (buying).[5]

When a (focal) firm is confronted with keen competition from its rival firms in the industry, it is bad news for the firm, which may in turn induce informed trading on that news. In this study, therefore, the conditional probability of informed trading on bad news (π_b) is the input variable to construct our measure of informed trading. Since we examine the effects of technology competition at a weekly frequency and Kogan et al. (2017) show that stock-market investors react to patent news mostly within a three-day window from Tuesday to Thursday, we compute in each week the average (π_b^w) of the daily probabilities (π_b's) from Tuesday to Thursday.[6] Because the measure of informed

[5] For a more detailed procedure for computing the three daily probability measures, see Brennan, Huh, and Subrahmanyam (2018).

[6] When we compute the average (π_b^w) of the daily probabilities within a week (from Tuesday to next

trading will be used as the dependent variable in regression analyses and π_b^w itself is bounded by [0, 1], we perform a logit-transformation of the raw measure (π_b^w) to obtain the (weekly) measure of informed trading on bad news, Π_b, as follows:[7]

$$\Pi_b = \ln\left(\frac{\pi_b^w}{1-\pi_b^w}\right). \tag{5}$$

In our subsequent analyses, this logit-transformed measure, Π_b, will be employed as our primary measure of informed trading in a firm facing technology competition.

2.2. The Measures of Technology Competition

We develop measures of technology competition at a firm level based on public information. We first collect patent records of all U.S. public firms from the updated NBER patent database, the patent data organized by Kogan et al. (2017), and the Harvard Business School patent inventor database of Li et al. (2014).[8] Our patent dataset covers all utility patents officially granted to public firms by the USPTO from 1976 to 2013.[9] It includes each patent's information about its application year-week, grant year-week, technology class, citations, and Compustat-matched identifiers (GVKEY) of its assignee (i.e., the firm that owns the patent) for each patent granted during the 1996-2013 period. Since the USPTO announces the contents of granted (i.e., approved) patents in the weekly *Official Gazette* on Tuesdays, the number of citations received by each firm's

Monday), our results are robust.

[7] For the issue of logit-transforming dependent variables, see Karolyi, Lee, and van Dijk (2012).

[8] The updated NBER patent data are available up to 2010 at: https://sites.google.com/site/ patentdataproject/Home.

[9] We use patent data instead of R&D expenses for the following reasons. First, patent data contain much richer information. It is difficult to interpret the implications of R&D expenses, which are the aggregated total of all R&D investments. Second, R&D investments cannot be appropriately priced or transferred. Third, managers have an incentive to manipulate 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,..., patent citations, and trademarks registered..." (p.32).

prior patents in each week is thus public information to all investors.

We first construct a measure of technology competition using the information about patent citations received by a (focal) firm and its rivals. For each (focal) firm in each year, we define its rivals as the 10 U.S. public firms with the highest product similarity scores. The product similarity scores are calculated by Hoberg and Phillips (2010, 2016) (HP) on an annual basis and are available since 1996. We count the number of citations received by a firm's patents using the reference list of new patents that are granted on Tuesday in each week. If a patent owned by the firm is cited by two newly granted patents, or if two of the firm's prior patents are cited by a newly granted patent, we count the case as two citations received by the firm.[10] We also calculate the number of citations received by each of its rival firms in a week in a similar approach. The number of citations reflects a firm's strength in its technology position revealed by the weekly *Official Gazette* (e.g., Jaffe, Trajtenberg, and Fogarty, 2000; Hall, Jaffe, and Trajtenberg, 2005a, 2005b). Therefore, in each week we compute the (innovation- or) competition-related measures based on the number of citations received as follows:

C_f: The measure of a focal firm's technology position, which is the natural logarithm of one plus the number of citations received by the focal firm in each week.

C_r: The measure of rival firms' technology position, which is the natural logarithm of one plus the HP-score-weighted average number of citations received in each week by 10 rivals (to a given focal firm) that have the highest HP-scores.[11]

[10] Patent A receives one citation when it is cited by Patent B in the latter's reference list in the granted patent section of an *Official Gazette* issue that announces the grant of Patent B. The reference list of a patent is prepared by both the applicants and examiners. In patent applications, patent applicants have a "duty of candor" to disclose any prior art (i.e., publication, patents, or any information sources in the public domain) that is material to "patentability" of their patent applications (i.e., novelty, non-obviousness, etc.). Failing to disclose all related prior arts may result in rejections of patent applications or invalidations from courts (Sampat, 2010; Roach and Cohen, 2013). Patent examiners conduct their independent searches, and add about 40% of citations (Thompson, 2006; Alcacer, Gittelman, and Sampat, 2009). The legal requirements and the active role of patent examiners ensure that the granted patent documents should cite all relevant patents (Campbell and Nieves, 1979; Trajtenberg, 1990).

[11] For example, if a firm has two rivals with the HP-scores of 0.5 and 0.3 and they receive four and two

C_{rmf}: The measure of a (focal) firm's technology competition, which is the difference between the two measures above (i.e., $C_{rmf} = C_r - C_f$). Thus, a firm with a higher value in C_{rmf} means that the (focal) firm experiences fiercer technology competition (or the firm is at a more serious disadvantage over its rivals) in the industry. We use C_{rmf} as the primary measure of technology competition. Since the number of citations is public information disclosed in the weekly *Official Gazette* on Tuesdays, the above measure of technology competition is not subject to any forward-looking bias.

The number of patents is a popular indicator for a firm's technology position in the literature (e.g., Griliches, 1981; Hall, 1993). We thus consider an alternative measure of technology competition based on the numbers of patents granted to a (focal) firm and its rival firms. For this purpose, each week we compute the following three variables:

P_f: The measure of a (focal) firm's technology position, which is the natural logarithm of one plus the number of patents granted to the focal firm in each week.

P_r: The measure of rival firms' technology position, which is the natural logarithm of one plus the HP-score-weighted average number of patents granted each week to 10 rivals (to a given focal firm) that have the highest HP-scores.[12]

P_{rmf}: The alternative measure of a (focal) firm's technology competition, which is the difference between the two measures above (i.e., $P_{rmf} = P_r - P_f$). So a firm with a higher value in P_{rmf} can be interpreted similarly to that in C_{rmf}.

We find that P_{rmf} does not reflect information about technology competition in a timely manner (compared to C_{rmf}), because the number of patents itself does not necessarily represent the quality of technology and, furthermore, patents granted to a firm in each week is sparser by nature: the frequency at which a firm obtains patents is much

citations respectively, the HP-score-weighted average number of citations is calculated as $\frac{(4\times0.5)+(2\times0.3)}{(0.5+0.3)} = 3.25$. Our results are robust to using a simple average of citations.

[12] Our results are robust to using a simple average number of patents granted to the rivals.

lower than the frequency at which a patent granted to or owned by the firm receives citations. For comparison purposes, however, we will also include P_{rmf} as one of the control variables in our empirical analyses.

2.3. Data, Control Variables, and Descriptive Statistics

To estimate the daily posterior probabilities of informed trading for NYSE/AMEX- and NASDAQ-listed stocks over the 18-year period (1996-2013), we process order flows using trades/quotes available from the NYSE Trades and Automated Quotations (TAQ) database. For the 1996-2006 period, the Lee and Ready (1991) algorithm is used to match trades with quotes and to classify each trade as buyer- or seller-initiated. For the 1996-1998 period we apply a five-second-delay rule to match trades with quotes. Considering the shorter reporting lag between trades and quotes in later years, we use a two-second-delay rule for the 1999-2006 period. Some issues related to applying the Lee-Ready method to the 'monthly' TAQ have been raised by researchers. Given that we lag quotes when matching with trades, classification errors may not be serious for the 1996-2006 period, in which high-frequency-trading volume is relatively low.

However, the past decade has witnessed significant changes in regulation, market structure, trading technologies, and trading behavior of market participants. Stoll (2014), for instance, documents that since the mid-2000s the number of daily trades has increased substantially while trade size has decreased, reflecting the prevalence of high-frequency trading (HFT), especially since 2007. Arnuk and Saluzzi (2012) argue that the introduction of the NBBO concept and Regulation NMS has made speed of execution very important in the U.S. stock market, triggering a surge of HFT. Easley, Lopez de Prado, and O'Hara (2012) and Holden and Jacobsen (2014) suggest that using the Lee-Ready (1991) method for the monthly TAQ database, which is time-stamped only to the second (as opposed to the millisecond), could lead to substantial classification errors due to large

HFT volume in recent years.

To reduce the classification errors, Holden and Jacobsen (2014) propose a low-cost alternative, which is applicable to the monthly TAQ database, and show that their algorithm provides more accurate classifications than the Lee-Ready (1991) method. Therefore, we employ the Holden-Jacobsen algorithm for the last seven years in our sample (2007-2013).[13] After matching trades and quotes based on either of the two algorithms, if a trade occurs above (below) the quote midpoint, it is considered buyer-initiated (seller-initiated). Trades and quotes in the TAQ database that are out of sequence, recorded before the open or after the close, or involved in errors or corrections are excluded.

The five *PIN*-model parameters, α, δ, μ, ϵ_B, and ϵ_S, are estimated *monthly* via the Hwang et al. (2013) method using a three-month rolling window. The monthly estimation allows us to calculate the parameters that incorporate the time-varying features of information events in a firm and trading activities based on those events. Given the monthly estimates of the five parameters, the *daily* posterior probability of informed selling (π_b) is then calculated using the numbers of buys (B) and sells (S) each day in the following month, using Eq. (4). The procedure is repeated for the 216 months from January 1996 to December 2013. We then obtain the weekly (Tuesday-Thursday) average measure (π_b^w) and its logit-transform (Π_b) for our analyses, as described above. The availability of the HP-scores limits the starting point of our sample period to 1996.

Table 1 reports descriptive statistics for the key variables. The cross-sectional value for each of the five statistics (mean, median, standard deviation (STD), skewness, and kurtosis) is first calculated each week and then the time-series average of those statistics is reported. The sample period is the past 921 weeks (1996-2013) for NYSE/AMEX-

[13] 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. So the time delay between quotes and trades is minimal (milliseconds at most). The Holden-Jacobsen (2014) algorithm uses all trades across different exchanges to find NBBO quotes and matches them with trades.

and NASDAQ-listed firms. We use ordinary common stocks only (SHRCD = 10 or 11 in CRSP). For most of the variables (except for the last two variables), the total number of firm-week observations used in this study over the 921 weeks is 2.29 million-2.61 million, depending on the availability of our variables. The average number of firms used in each week is 2,487.6-2,832.3.

The upper part of the table shows that the conditional probability of informed trading on bad news (π_b^w) is 0.144, and its logit-transform (Π_b) is -17.849 on average over the 921 weeks. It also reports the statistics for the measures of technology competition for a focal firm (C_{rmf} and P_{rmf}) as well as the measures of technology position separately for a focal firm (C_f and P_f) and its rivals (C_r and P_r). Given the paucity of granted patents on a weekly basis, the average numbers of patents granted to a focal firm ($P_f = 0.038$) and its rival firms ($P_r = 0.062$) are much smaller than those of citations received by a focal firm ($C_f = 0.190$) and its rivals ($C_r = 0.249$). The technology position variables in a focal firm also have lower values on average than those in its rivals ($C_f < C_r$ and $P_f < P_r$), since the variables for the rivals are averaged across its 10 most competitive rival firms. Consequently, the average values in the measures of technology competition for a focal firm (C_{rmf} and P_{rmf}) are slightly positive (0.059 and 0.024, respectively). We also note that C_{rmf} and P_{rmf} are negatively skewed, suggesting that highly negative values in the two metrics (which in turn means that a focal firm is at a strong advantage over its rivals in technology competition) are concentrated among a few (focal) firms.

In investigating the relations between technology competition and informed trading below, we control for the effects of firm characteristics in a (focal) firm as well as its rival firms. The control variables for a focal firm is distinguished by subscript 'f' and those for its rival firms are computed as the HP-score-weighted average across its 10 rivals and indicated by subscript 'r'. The control variables are defined and constructed as follows:

dIH: The monthly change in the fraction of the total (direct and indirect) insider holdings

(IH) relative to the total 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. We use the change in insider holdings (dIH) because it is more relevant to insider-trading activities than IH itself.

NANA: The number of analysts following a firm on a monthly basis, which is available from the I/B/E/S database. 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 evidence that research activities by analysts may increase information asymmetry and hence informed trading in a firm, because analysts often disseminate research results selectively to their clients.[14]

R&D: The ratio 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, and usually lead to information asymmetry associated with innovating activities

[14]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..."

(Aboody and Lev, 2000; Aslan et al., 2011; Seru, 2014).

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

LEV: The leverage ratio calculated as the ratio of liabilities to assets (both in \$million) at the quarter-end. This variable is obtained from Compustat (Fundamentals Quarterly). A higher value in *LEV* implies a greater level of default risk in a firm.

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 a higher level of information asymmetry.

RVOLA: The weekly standard deviation of daily stock returns within a week. This measure of return volatility (computed from CRSP) is used as a proxy for the arrival rate of information.

Most of the control variables are not available on a weekly basis. So those lower-frequency variables are obtained at the end of the previous month or quarter, and then the values are assigned to the weeks within the following month or quarter (hence those variables are lagged and constant across several weeks). The middle part of Table 1 shows the statistics for the control variables. Quarterly R&D expenses relative to assets (*R&D*) for a focal firm (for its rivals) is on average 1.2% (1.1%) in the sample. The average book-to-market ratio (*BTM*) is 0.705 (0.664). The average change in insider holdings (*dIH*) is -0.026 (-0.026), implying that insiders are more likely to sell than to buy in general. The weekly return volatility (*RVOLA*) is 3.1% (3.1%). The number of analysts that follow a firm (*NANA*) is 4.67 (5.23) on average. The average of the leverage ratio (*LEV*) is 0.524 (0.547).

To analyze the return predictability of technology competition via informed trading on bad news in the later part of the paper, we compute factor (F)-adjusted cumulative abnormal returns (CARs) in basis points (bps) over three trading days from Tuesday (patent announcement date) to Thursday within each week. For each of the three days (day d) within a week, a factor beta(s) is (are) first estimated from the time-series regression of the daily excess return (the daily raw return, R_i, minus the one-month T-bill rate, R_f) on the (one, three, or four) factor(s) over the window from day d-260 to day d-11. With the estimated factor betas (β's) available, the daily abnormal return (AR) for day d is obtained as AR $= (R_i - R_f) - \sum_{k=1}^{K} \widehat{\beta}_k F_k$. Then a CAR is the sum of ARs over the three trading days (Tuesday-Thursday). Three different CARs over the three trading days around the patent announcement date are defined as follows:

CAR_{mkt}: The cumulative abnormal return, adjusted for the market factor (MKT $= R_m - R_f$, where R_m is the CRSP value-weighted daily index return).

CAR_{ff3}: The cumulative abnormal return, adjusted for the Fama-French (1993) three factors (MKT, SMB, and HML).

CAR_{ff4}: The cumulative abnormal return, adjusted for the Fama-French (1993) three factors (MKT, SMB, and HML) and the Carhart (1997) momentum factor (UMD).

Daily stock returns are obtained from CRSP, and the daily Fama and French (1993) three factors, one-month T-bill rate, as well as the Carhart (1997) momentum factor are collected from Kenneth French's website. The lower part of Table 1 shows that the average number of stocks used in each week is 2,487.6 and that the CARs range from 11.101 bps to 15.343 bps on average.

Last, we examine using Abel Noser Solutions (also known as the 'ANcerno' database) who is more active in trading on the news about technology competition and whether they make any profit from such trading. We thus construct a variable for each institutional investor's weekly net selling (in %) of a given firm's common shares (denoted as INS), computed as the dollar value of shares sold by an institution minus the dollar value of shares bought by the same institution from Tuesday to Thursday, scaled by the sum of the two. We also track down each institutional investor's return (in bps) from trading shares in a given focal firm over the Tuesday-Thursday period (denoted as ITR). For this, we first obtain a cumulative stock return for each trade by an institutional investor using ANcerno, and then compute the principal-weighted average return across all trades made by the same institutional investor to obtain ITR.[15]

The sample period for the analyses on institutional investors' trading activities reduces to 1997-2010 (696 weeks), since trackable institution identities are available only in that period in ANcerno. The bottom part of Table 1 reports that the total number of institution-firm-week observations over the 696 weeks is 3,260,242, and the average number of firm-institutions used in each week is 4,684.3. We find that the average value in institutional investors' net selling (INS) is -5.129%, and the average return associated with their trading activities (ITR) is 7.115 bps.

3. Technology Competition and Informed Trading

3.1. Baseline Regressions

When a firm has a highly positive value in a technology-competition measure (C_{rmf} or P_{rmf}), it means that the firm is confronted with stiffer technology competition from its rival firms or is at a serious disadvantage in technology relative to its rivals, which in turn can be interpreted as bad news for the firm. In this situation, sophisticated investors

[15] Abel Noser Solutions (or 'ANcerno') is a consulting firm providing "a range of effective trading services and trade analytics globally to institutional asset owners, investment managers and brokers." Their Institutional clients send their complete transaction records to Abel Noser Solutions for trading cost analyses. This dataset includes a significant portion of institutional trading volume (see Puckett and Yan, 2011) and is widely used in academic research on institutional trading (e.g., Puckett and Yan, 2011; Hu, McLean, Pontiff, and Wang, 2013; Goetzmann, Kim, Kumar, and Wang, 2014). For each transaction record, this database provides 109 variables including the time of trade, CUSIP of the stock traded, the execution price, the number of shares traded, and the direction of the trade (buy or sell).

may try to take advantage of the bad news by trading shares of the firm. To examine the effects of technology competition in a firm on informed trading, therefore, we employ the measure of informed trading on bad news (π_b^w or its logit-transform, Π_b).

Specifically, we first conduct baseline panel regressions using the variables obtained on a weekly basis over the 921 weeks from 1996 to 2013 as follows:

$$\Pi_{b,it} = \phi C_{rmf,it} + \gamma P_{rmf,it} + \sum_{n=1}^{N} b_n X_{n,it} + \omega_i + \tau_t + \epsilon_{it}, \tag{6}$$

where $\Pi_{b,it}$ is the measure of informed selling on bad news (computed over the Tuesday-Thursday period) for (focal) firm i at week t; $C_{rmf,it}$ is our primary measure of technology competition (computed as of Tuesday) for firm i at week t constructed based on the number of citations; $P_{rmf,it}$ is the alternative measure of technology competition constructed (as of Tuesday) based on the number of patents; $X_{n,it}$ includes the control variables (*dIH, NANA, R&D, ROA, LEV, BTM,* and *RVOLA*) for focal firm i (indicated by subscript 'f') and/or its 10 rival firms (HP-weighted average across rival firms) (indicated by 'r'); ω_i is the firm fixed effect; and τ_t is the year-week fixed effect.

Note that while time subscript 't' is used for most of the variables in Eq. (6), $\Pi_{b,it}$ is led in time relative to the key explanatory variables. Especially, given that most of the control variables ($X_{n,it}$) are not available on a weekly basis, they are obtained at the end of the previous month or quarter and then the values are assigned to the weeks within the following month or quarter (hence lagged). Since the extent of information asymmetry and informed trading may differ across firms due to unobservable firm characteristics, we control for the firm fixed effects throughout our analyses. In addition, we consider the year-week fixed effects to control for technology cycles or its time-series patterns. We compute cluster-robust standard errors and t-values at the firm level in all regressions to get around the possible error correlations within each firm.

The regression results are reported in Table 2. Panel A uses original (raw) variables, while Panel B uses standardized variables in order to facilitate the evaluation of the relative importance among the variables. In Panel A, the number of observations (*Obs*) used in the regressions is about 2.61 million firm-weeks. The adjusted R-squared (*AdjR-sqr*) in the regressions ranges from 36.1% to 36.9%. Specification (1) in Panel A shows that C_{rmf} is strongly positively associated with Π_b after controlling for the firm and year-week fixed effects, suggesting that a firm facing fiercer technology competition from its rival firms (i.e., a firm being at a more serious disadvantage in technology over its rivals) experiences more informed trading (selling of common shares) on the bad news during the week. To get a feel for the economic impact of technology competition on informed trading, we find in specification (1) of Panel A that a one-standard-deviation increase in C_{rmf} (0.57) is associated with an increase in Π_b of 1.68, which is equivalent to a 9.41% increase (in absolute terms) relative to the sample average of Π_b (-17.849) and an increase that constitutes 7.8% of its standard deviation (21.42).

The alternative measure of technology competition (P_{rmf}), which is based on the number of granted patents, does not reflect information about technology competition in a timely fashion (compared to C_{rmf}) for the reasons discussed earlier. For comparison purposes, however, we include it in specifications (2)-(4). We find in specifications (2) and (3) that the coefficient on the patent count-based competition measure is also positive and statistically significant at the 10% level (or better), after controlling for the seven firm characteristics of the focal firms. When the firm characteristics of the rival firms are included at the same time in specification (4), however, the impact of P_{rmf} becomes insignificant. In any case, our baseline results leave no doubt that when a focal firm faces stiffer technology competition measured by C_{rmf}, which better incorporates the quality of patents, informed investors are more actively engaged in trading (selling) common shares of the firm.

Briefly mentioning the effects of the control variables, we find in specifications (3) and (4) that $R\&D_f$ and LEV_f are positively and significantly associated with Π_b, given that larger R&D expenses and higher leverage in a focal firm lead to more information asymmetry (see Aboody and Lev, 2000) and a higher possibility of default in the firm. The coefficient on $NANA_f$ is negatively significant in the two specifications, indicating that a (focal) firm with broader analyst coverage is subject to less informed trading, probably because broader coverage tends to reduce information asymmetry in the firm. By contrast, specification (4) shows that the effect of analyst coverage in its rival firms ($NANA_r$) on the focal firm's informed trading works in the opposite direction. Higher return volatility in a focal firm ($RVOLA_f$) as well as in its rivals ($RVOLA_r$) is negatively associated with Π_b, making informed trading more difficult in the focal firm. The positive coefficient on dIH_f implies that insiders in a focal firm are more likely to sell than to buy its shares, consistent with the (negative) average of dIH in Table 1.

As to the standardized regression results in Panel B, the impact of C_{rmf} on Π_b is much greater than that of P_{rmf}. In specification (3), for instance, the magnitude (0.012) of the coefficient on P_{rmf} is only 18.8% compared to the coefficient on C_{rmf}. Notable is that the impact of analyst coverage in focal firms ($NANA_f$) is relatively large. For other variables, the patterns are qualitatively similar to those observed in Panel A.

3.2. Robustness Checks

3.2.1. With Five Rival Firms

In the above baseline analysis, C_{rmf}, P_{rmf}, and X_n (for rivals) shown in Eq. (6) are all constructed based on the values from 10 rival firms that have the highest HP-scores in the industry. Here we check whether our results are affected when only five rival firms are used to construct the above variables. The results are reported in Table 3.

By narrowing down the number of rival firms from 10 to five in Table 3, the number of observations (firm-weeks) (Obs) decreases by about 7.92% compared with Panel A in Table 2. While the magnitude of the coefficient on C_{rmf} decreases by 21%-24%, the relations of C_{rmf} to Π_b are positive and statistically significant at the 1% level in any case, confirming that a firm at a relative disadvantage in technology over its rivals is vulnerable to informed trading on bad news. We find a similar feature in P_{rmf} so that the coefficient of it is no longer significant when the control variables are included in the regressions. This also suggests that C_{rmf} is a better variable to measure the status of a firm's competitive edge in technology. As for the effects of the control variables on informed trading, the patterns in Table 3 are virtually the same as those observed in Panel A of Table 2.

Since we believe that using a broader set of rival firms is more suitable for constructing the variables mentioned above (especially C_{rmf} and P_{rmf}), in the remaining analyses we will continue to use C_{rmf}, P_{rmf}, and X_n that are constructed with 10 rival firms.

3.2.2. With Technology Positions Separately for Focal and Rival Firms

To investigate which firm's (focal vs. rival) technology position contributes more to informed trading in a focal firm, we conduct regressions, where the technology positions of focal firms and their rival firms are separately specified. We thus estimate the following regression controlling for the firm and year-week fixed effects:

$$\Pi_{b,it} = \varphi_f C_{f,it} + \varphi_r C_{r,it} + \gamma_f P_{f,it} + \gamma_r P_{r,it} + \sum_{n=1}^{N} b_n X_{n,it} + \omega_i + \tau_t + \epsilon_{it}, \tag{7}$$

where $C_{f,it}$ is the measure of a citation-based technology position for (focal) firm i at week t; $C_{r,it}$ is the equivalent for firm i's 10 rivals; $P_{f,it}$ is the measure of a patent count-based technology position for (focal) firm i; and $P_{r,it}$ is the equivalent for firm i's 10 rivals. All these have been defined in Section 2.2.

As shown in Table 4, the number of citations received by a focal firm (C_f) is negatively associated with the measure of informed selling (Π_b), while that received by its rivals (C_r)

is positively associated with Π_b. These findings are consistent with our baseline results in Table 2: when a focal firm receives fewer citations and its rivals receive more citations (both are bad news for the focal firm), the focal firm is subject to more informed selling on the news. Interestingly, although the bad news in a focal firm (i.e., fewer citations) and that in its rival firms (i.e., more citations) causes informed selling in shares of the focal firm, we find that the effect of the rivals' technology position on informed trading is stronger than that of the focal firm itself, as the size (in absolute terms) of the coefficient on C_r is much larger than that on C_f by a factor of 5 to 6. The above finding implies that when it comes to corporate innovating activities, evaluating them from a relative perspective offers more insights.

Consistent with the role of P_{rmf} reported in Tables 2 and 3, the coefficients on P_f and P_r are not statistically significant, suggesting again that the measures of technology position that are constructed with the number of patents exhibit weaker explanatory power for informed trading.

3.2.3. Excluding Self-Citations and Citations Received by Expired Patents

We consider other alternatives in counting patent citations for constructing the measures of technology competition. A firm has a higher chance to cite patents already owned by itself due to its familiarity or expertise in technology. However, such self-citations may induce biases to the measure of technology competition. Therefore, we exclude self-citations when constructing C_{rmf} for the analyses using Eq. (6) in Panel A of Table 5. The panel shows that excluding self-citations does not change much the explanatory power of C_{rmf} for informed selling, compared to that in the corresponding specifications reported in Panel A of Table 2. Noteworthy is that by excluding self-citations, the other measure of competition (P_{rmf}) now plays a stronger role, with its coefficient being significant even after controlling for the rivals' characteristics in specification (4).

If a patent owned by a firm expired, it means that the technology related to the patent is out of date or less valuable for the firm. This in turn implies that the information from citations it receives is likely to be stale. It is because expired patents no longer generate any profit for the owner firms, which makes the citations they receive less informative for their cash flows and stock prices. In Panel B of Table 5, we thus estimate Eq.(6) using C_{rmf} that is constructed after excluding the citations received by expired patents. We find in the panel that the impact of C_{rmf} (and P_{rmf} as well) is by and large comparable with that in the corresponding specifications reported in Panel A of Table 2.

4. Further Identification Tests

One concern is that our baseline results in Table 2 may be subject to endogeneity issues such as reverse causality and omitted variables. However, there is no reason to believe that causality flows in the opposite direction in our analyses: it is unconvincing to believe that informed trading that occurs during the Tuesday-Thursday period within a given week causes new citations that a (focal) firm receives on Tuesday in that week. These new citations announced on Tuesday have been inserted by patent applicants and further added by USPTO examiners long before the announcement date. Although it is possible that informed trading is persistent and affects future citations that the firm will receive, controlling for the firm fixed effects should mitigate the influence of persistence.

There may be industry- or firm-level omitted variables that influence both informed trading and news about patent citations, which could lead to positive relations between the two variables. For example, omitted variables related to technology cycles or time-series patterns in informed trading might potentially bias our estimations. However, we have considered both firm and year-week fixed effects in all our regression analyses to alleviate the concerns about firm-level or time-varying omitted variables. Moreover, an unreported table shows that the results are robust when we control for the industry and year-week joint effects, which soaks up any time-varying industry-specific variations in informed trading. Thus, we do not believe that our findings are mainly driven by omitted industry-specific variables. We have also considered an extensive list of control variables for focal firms and their rivals, which mitigates the concern about omitted variables.

However, although we include many plausible determinants of informed trading, we cannot rule out the possibility of certain firm-level omitted shocks that might result in the positive relation between informed trading and bad news about innovating capabilities. In this section, therefore, we address the potential issue of firm-level omitted variables by conducting two-stage least squares (2SLS) regressions.

4.1. A Base Case: OLS Regressions Using the Measure Constructed with Citations Made by Applicants Only

For 2SLS regressions, we first distinguish citations inserted by patent applicants from those added by patent examiners in the USPTO. Patent examiners in the USPTO make their own search and play an important and impartial role in adding relevant citations to patent applications (Thompson, 2006). In fact, about 40% of citations are added by patent examiners (Alcacer, Gittelman, and Sampat, 2009). These citations are purely based on technological relevance, and are not driven by information related to other aspects of a firm (such as its stock prices and firm value). Thus, we believe that if there is any omitted variable driving our result, such a variable should affect the citations inserted by applicants but *not* those added by USPTO examiners.

The data on whether citations are inserted by applicants or added by examiners are available from 2002 only, so our identification test will be limited to the 2002-2013 period.[16] For the test, we construct the measures of technology position based on the number of citations that are made by applicants (examiners) and received by a focal firm

[16] We conduct analyses similar to those reported in Table 2 for the 2002-2013 period and find that the results (unreported) remain robust.

as well as by rival firms, which are denoted as C_f^{app} (C_f^{exa}) and C_r^{app} (C_r^{exa}), respectively. These allow us to compute technology competition measures C_{rmf}^{app} and C_{rmf}^{exa} that are based on the number of citations made by applicants and by examiners, respectively.

As a base-case analysis, we first test using OLS regressions as in Eq. (6) whether C_{rmf}^{app} can explain Π_b in the subsample period. Table 6 shows that the coefficient on C_{rmf}^{app} is positively significant at the 5% or better all across four specifications. This suggests that if there is any omitted variable that affects C_{rmf} in Table 2, it should also affect C_{rmf}^{app} in Table 6. We next obtain fitted values of C_{rmf}^{app} for 2SLS regressions below.

4.2. Two-Stage Least Squares Regressions with an Instrumental Variable

The measure of technology competition based on the number of citations made by examiners, C_{rmf}^{exa}, is used as an instrumental variable (IV) for C_{rmf}^{app} constructed as above. We find that C_{rmf}^{exa} is highly correlated with C_{rmf}^{app}, which satisfies the relevance condition for an IV. Furthermore, since USPTO examiners add citations purely from a technological perspective without being aware of the implications for the firm's stock prices, C_{rmf}^{exa} is not directly related to any non-technological aspect of the patent and the firm (e.g., stock prices, trading activities, etc.). Therefore, the exclusion restriction is likely satisfied.

Table 7 reports the results of the 2SLS regressions. In the first stage (the left column in each of the four specifications), we regress C_{rmf}^{app} on the IV (i.e., C_{rmf}^{exa}) as well as other control variables used in Eq. (6) to predict C_{rmf}^{app}. The coefficient on C_{rmf}^{exa} in the first-stage regression is positively significant at 1% in any case, indicating that the examiner-based competition measure can explain the applicant-based competition measure.

We then use the fitted (or predicted) values of C_{rmf}^{app} (denoted as $Fitted\_C_{rmf}^{app}$.) obtained in the first-stage regression as one of the explanatory variables in the second-stage regression (the right column in each specification). Note that this fitted variable is purged of all firm-level omitted variables, because they are estimated in the first-stage regression that contains only observable variables, including the instrumental variable, control variables, and fixed effects. In the second stage, we regress Π_b on $Fitted\_C^{app}_{rmf}$ and other control variables. Therefore, the coefficient on $Fitted\_C^{app}_{rmf}$ in the second-stage regression represents the impact of the focal firm's technology competition on informed trading free of firm-level omitted variables. We find in the second stage that the coefficient on $Fitted\_C^{app}_{rmf}$ is positive and statistically significant across all four specifications.

In the lower part of each specification, we report the *rk LM*-statistic (*Kleibergen-Paap Stat*) from the Kleibergen-Paap (2006) under-identification test for the relevance of the IV. The p-values confirm the validity of the instrumental variable, as the under-identification test always rejects the null hypothesis of "no relevance," meaning that the proposed IV can explain our technology competition measure. To sum up, our analyses in Table 7 support the hypothesis that unfavorable news about technology competition causes informed selling, after we rule out the potential influence of omitted variables.

5. The Return Predictability of Technology Competition

In this section, we examine whether the intensity of technology competition (measured as of Tuesday) can predict subsequent stock returns (computed over the Tuesday-Thursday period). To see if informed traders are able to profit from their trading on the bad news, we estimate the following panel regressions:

$$CAR_{i,t} = \phi C_{rmf,it} + \psi P_{rmf,it} + \sum_{n=1}^{N} b_n X_{n,it} + \omega_i + \tau_t + \epsilon_{it}, \tag{8}$$

where $CAR_{i,t}$ is the cumulated abnormal return (CAR) on firm i's stock over the three trading days (Tuesday-Thursday) at week t. According to Kogan et al. (2017), major price reactions to patent announcements occurs within the three-day window, which is why $CAR_{i,t}$ is computed over the Tuesday-Thursday period in each week.

As described in Subsection 2.3, we compute factor (F)-adjusted CARs in basis points (bps). For each of the three trading days (day d) within a week, factor β's are first estimated from the time-series regression of the daily excess return $(R_i - R_f)$ on the (one, three, or four) factor(s) over the window from day d-260 to day d-11. With the estimated β's available, the daily abnormal return (AR) for day d is obtained as AR $=$ $(R_i - R_f) - \sum_{k=1}^{K} \widehat{\beta}_k F_k$, where F includes the market excess return (MKT), the Fama-French (1993) three factors (FF3: MKT, SMB, and HML), or the four factors [FF4: FF3 and Carhart's (1997) momentum factor (UMD)]. Then a (risk-adjusted) CAR is the sum of ARs over the three trading days (Tuesday-Thursday).

We report the results in Table 8 using three different CARs, denoted as CAR_{mkt}, CAR_{ff3}, and CAR_{ff4}. For brevity, we report only the specifications that control for firm characteristics. We find in the table that C_{rmf} is strongly negatively associated with CARs, demonstrating that the disadvantageous status in competition (or fiercer technology competition) predicts lower subsequent stock returns in a firm. In specification (1) in Panel A, for example, a one-standard-deviation increase in C_{rmf} (0.57) predicts the cumulative abnormal return (CAR_{mkt}) lower by 1.89 bps in the three-day period, when the return is adjusted using the one-factor (MKT) model. The results are consistent across all specifications in Panels A-C, regardless of whether rivals' control variables are included, or the return is risk-adjusted via the three- or four-factor model.

In summary, the analyses in this section provide evidence that competition-related patent news in a firm has predictive power for its stock returns, implying that informed investors can make profits (before trading costs) from selling on the bad news related to the firm's technology competition. This also suggests that informed traders' trading activities are the channel through which the information about corporate innovation or technology competition in the firm is effectively impounded in its stock prices.

6. Who is Active in Informed Trading on the News about Technology Competition?

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 or technology competition? We propose that institutional investors are more informed in general than retail investors on technology competition and thus trade actively on the news accordingly.[17] To test this proposition, we utilize institutional trading data from Abel Noser Solutions ('ANcerno'), which has been used to examine institutional investors' trading patterns (Puckett and Yan, 2011; Hu, McLean, Pontiff, and Wang, 2013; Goetzmann, Kim, Kumar, and Wang, 2014). Using the ANcerno database (available for 1997-2010), we track down each institutional investor's sell-buy imbalance (i.e., net selling): that is, for a given firm, we compute the dollar volume of each institution's selling minus the dollar volume of the same institution's buying, scaled by the sum of the two values. We label this variable as *INS*.

If institutional investors are active in trading on the news about a firm's technology competition, we expect that institutions' net selling of the firm's shares will increase during the week in which institutional investors receive unfavorable news about the firm's competitive edge. To formally test this, we estimate the following regression:

$$INS_{i,j,t} = \varphi C_{rmf,it} + \theta P_{rmf,it} + \sum_{n=1}^{N} b_n X_{n,it} + \omega_i + \iota_j + \tau_t + \epsilon_{i,j,t}, \tag{9}$$

[17] 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 (e.g., 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.

where $INS_{i,j,t}$ is institutional investor j's net selling (in %) of shares in firm i over the three trading days (Tuesday-Thursday) at week t. As defined earlier, $C_{rmf,it}$ is the patent citation-based technology competition measure and $P_{rmf,it}$ is the patent count-based competition measure (both are calculated as of Tuesday). We include in Eq. (9) the firm characteristics of the firm and/or its rivals, together with the three types of fixed effects: institution (ι_j), firm (ω_i), and year-week (τ_t). For reliable statistical inferences, we obtain t-values that are cluster-robust at the firm and institution levels.

Table 9 shows that the number of observations (Obs) used for this analysis is 3.26 million institution-firm-weeks. We find in the table that C_{rmf} is positively associated with *INS*, with its coefficient being significant at the 5% level in any case: i.e., the more unfavorable is the news about a firm's technology competition, the more shares of the firm institutional investors sell. This finding supports our proposition that institutional investors react to the bad news about a firm's competitive edge (revealed by the weekly *Official Gazette* on Tuesday) by selling shares of the firm. To get a sense of its economic impact, we find in specification (3) of Table 9 that with a one-standard-deviation increase in C_{rmf} (0.57), institutional investors increase their net selling (*INS*) in the week by 0.5 percentage point, which is equivalent to a 9.7% increase relative to *INS*'s sample average (in absolute terms) (5.129).

Given the fact that institutional investors are indeed active in trading on the news about technology competition, our last question is whether they can profit from such trading. To answer this question, we calculate each institutional investor's trading return (denoted as *ITR*) (in basis points) from selling shares of a given focal firm. For this, using ANcerno we first obtain a cumulative stock return based on the execution price and the Thursday close price for each trade made by an institutional investor, following Puckett and Yan (2011). We then compute the principal-weighted average return across all trades made by the same institutional investor from Tuesday to Thursday within each week. Using ITR as the dependent variable, we estimate the following regression:

$$\begin{aligned} ITR_{i,j,t} &= \eta INS_{i,j,t} + \varphi H_{C,it} + \gamma INS_{i,j,t} * H_{C,it} \\ &\quad + \theta P_{rmf,it} + \sum_{n=1}^{N} b_n X_{n,it} + \omega_i + \iota_j + \tau_t + \epsilon_{i,j,t}, \end{aligned} \tag{10}$$

where $ITR_{i,j,t}$ is institutional investor j's trading return from trading shares in firm i at week t, $H_{C,it}$ is a dummy variable set at 1 if C_{rmf} for firm i is in the 90th percentile and 0 otherwise, and $INS_{i,j,t}$*$H_{C,it}$ is the interaction term between $INS_{i,j,t}$ and $H_{C,it}$. We include the interaction term to capture the effect of institutional investors' net selling when a firm is confronted with stiffer competition in technology.

Table 10 presents the regression results for four specifications with the interaction terms as well as the other four without it. It is reasonable to see in specifications (1), (3), (5), and (7) that greater institutional net selling of a firm's shares (INS) generally predicts a lower return from trading its shares (ITR). Keener competition in a firm (H_C) is also negatively related to the institutional trading return on its shares, albeit statistically insignificant. However, our focus is more on the interaction term. As can be seen in specifications (2), (4), (6), and (8), the coefficient (γ) on $INS_{i,j,t}$*$H_{C,it}$ is positively significant at the 1% level in any case, which suggests that when the firm is at a serious disadvantage over its rivals in technology competition, institutional net selling of its shares is positively associated with their trading return.[18]

The results presented in Tables 9 and 10 collectively suggest that some institutional investors are informed traders who actively assess a firm's status in technology competition on a weekly basis and capitalize on their information advantage through trading activities. On balance, our findings strongly support the notion that institutional investors' trading activities are an important channel through which the information about a firm's

[18] When we use C_{rmf} itself (instead of a dummy variable) as well as the 50th or 75th percentile for H_C in Eq. (10), the results are qualitatively similar.

technological innovation or competition is impounded in its stock prices.

7. Conclusion

Despite the fact that technology competition has long been recognized as an essential factor of success and sustainability of corporations, the channel through which the status of their competitive edge is reflected in stock prices or whether in practice investors assess it and trade securities based on such information remains unexplored in the literature. It is partly because of difficulties in estimating or obtaining appropriate proxies for informed trading and technology competition. To examine these issues, we construct a patent citation-based measure of technology competition on a weekly basis as well as a high-frequency measure of informed trading.

Our empirical results show that a firm facing fiercer competition from its rival firms (i.e., being at a greater disadvantage over its rivals in technology competition) experiences more informed selling on the bad news in a given week. Our results are robust to controlling for a battery of variables related to information asymmetry, as well as for the firm and year-week fixed effects, and to using alternative proxies for technology competition. These findings support the hypothesis that competition-related news is indeed an important determinant and predictor of informed trading in financial markets. We address endogeneity issues by conducting 2SLS regressions using an instrumental variable devised based on the citations inserted by patent examiners.

In addition, we find that a firm's unfavorable status in technology competition released on Tuesday predicts its subsequent stock returns in that week, and informed trading on such news is profitable. In particular, we provide convincing evidence using the data on stock transactions by institutions that institutional investors actively assess the status of firms' technology competition and capitalize on their informational advantage through trading activities, achieving higher returns.

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Table 1
Descriptive Statistics for the Key Variables

This table reports descriptive statistics [mean, median, standard deviation (STD), skewness, kurtosis, total number of observations (i.e., firm-weeks or institution-firm-weeks) (*Obs*), and weekly average number of observations (i.e., firms or firm-institutions) (*Weekly Obs*)] for the key variables. The cross-sectional value for each of the five statistics is first calculated each week and then the time-series average of those statistics is reported. The sample includes ordinary common stocks (SHRCD = 10 or 11 in CRSP) for NYSE/AMEX- and NASDAQ-listed stocks over the 18-year period (1996-2013: 921 weeks). The informed trading measure is defined as follows. Π_b: the logit-transform of π_b^w [i.e., $\ln\left(\frac{\pi_b^w}{1-\pi_b^w}\right)$], where π_b^w is the average of daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that bad-news information event occurs (π_b) over three trading days from Tuesday to Thursday within each week. To process order flows used in the above variable, intradaily trades and quotes from 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 2013. Technology- and competition-related variables are defined as follows. C_f: the natural logarithm of one plus the number of citations received by a (focal) firm in each week; C_r: the natural logarithm of one plus the HP-score-weighted average number of citations received in each week by ten rival firms that have the highest HP-scores, where the HP-scores are the product similarity scores calculated by Hoberg and Phillips (2010, 2016) (HP) on an annual basis and available since 1996; C_{rmf}: the difference of the above two variables (i.e., $C_r - C_f$), which is the measure of technology competition (or relative disadvantage in technology) for a focal firm; P_f: the natural logarithm of one plus the number of patents granted to the focal firm in each week; P_r: the natural logarithm of one plus the HP-score-weighted average number of patents granted in each week to 10 rivals that have the highest HP-scores; and P_{rmf}: the difference between the two measures (i.e., $P_r - P_f$), which is an alternative measure of technology competition for a focal firm. Control variables for a focal firm (indicated by subscript '*f*') as well as for its rival firms (indicated by subscript '*r*') (which is obtained as the HP-score-weighted average of the control variables across its rival firms) are defined as follows. *dIH*: the monthly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding; *NANA*: the monthly number of analysts following a firm; *R&D*: the ratio of quarterly research and development expenses (in $million) to quarter-end assets (in $million), and 0 if the expense is missing; *ROA*: the ratio of quarterly net income (in $million) to quarter-end assets (in $million), or 0 if missing; *LEV*: the leverage ratio calculated as ratio of total liabilities to the assets at the quarter-end; *BTM*: the ratio of quarter-end book value (in $million) to quarter-end market capitalization (in $million); and *RVOLA*: the weekly standard deviation of daily stock returns within a week. To compute factor (*F*)-adjusted cumulative abnormal returns (CARs) (in basis points) over three trading days from Tuesday to Thursday within each week, for each of the three days (day *d*), a factor beta(s) and the intercept are first estimated from the time-series regression of the daily excess return (the raw return minus the one-month T-bill rate) on the (one, three, or four) factor(s) over the window from day *d*-260 to day *d*-11. With the estimated $\hat{\beta}$'s available, the daily abnormal return (AR) for day *d* is obtained as AR = the daily excess return - $\sum_{k=1}^{K}\hat{\beta}_k F_k$. Then a CAR is the sum of ARs over the three trading days (Tuesday-Thursday). CARs are defined as follows. CAR_{mkt}: CAR adjusted for the market factor (MKT = $R_m - R_f$); CAR_{ff3}: CAR adjusted for the Fama-French (1993) three factors (MKT, SMB, and HML); and CAR_{ff4}: CAR adjusted for the Fama-French (1993) three factors (MKT, SMB, and HML) and the Carhart (1997) momentum factor (UMD). Two more variables related to institutional investors' trading activities are defined as follows. *ITR*: each institutional investor's trading return (in basis points) from trading shares in a given focal firm over the Tuesday-Thursday period (calculated using the ANcerno database from 1997 to 2010), for which a cumulative stock return based on the execution price and the Thursday close price is first obtained for each trade made by an institutional investor, and then the principal-weighted average return is computed across all trades made by the same institution from Tuesday to Thursday within a week; and *INS*: each institutional investor's weekly net selling (in %) of shares in a given focal firm from Tuesday to Thursday, calculated (using ANcerno) as the dollar volume sold by each institution minus the dollar volume bought by the same institution in a firm, scaled by the sum of the two values. *ITR* and *INS* are available for 1997-2010 (696 weeks).

(Table 1: continued)

Descriptive Statistics for Key Variables							
Variables	Mean	Median	STD	Skewness	Kurtosis	Obs	Weekly Obs
π_b^w	0.144	0.011	0.22	1.66	5.44	2,608,575	2832.33
Π_b	-17.849	-9.450	21.42	-1.39	4.31	2,608,575	2832.33
C_f	0.190	0.000	0.62	4.26	24.18	2,608,575	2832.33
C_r	0.249	0.041	0.40	2.38	10.73	2,608,575	2832.33
C_{rmf}	0.059	0.000	0.57	-2.30	17.82	2,608,575	2832.33
P_f	0.038	0.000	0.21	7.08	65.26	2,608,575	2832.33
P_r	0.062	0.000	0.13	3.24	17.89	2,608,575	2832.33
P_{rmf}	0.024	0.000	0.22	-3.57	39.69	2,608,575	2832.33
dIH_f	-0.026	0.000	1.72	-1.18	55.56	2,608,575	2832.33
$NANA_f$	4.67	2.77	5.47	1.74	6.46	2,608,575	2832.33
$R\&D_f$	0.012	0.000	0.03	8.79	172.18	2,608,575	2832.33
ROA_f	-0.007	0.006	0.10	-9.68	282.29	2,608,575	2832.33
LEV_f	0.524	0.520	0.27	0.88	33.12	2,608,575	2832.33
BTM_f	0.705	0.549	1.76	6.84	188.34	2,608,575	2832.33
$RVOLA_f$	0.031	0.024	0.03	5.09	78.05	2,608,575	2832.33
dIH_r	-0.026	-0.001	1.18	-0.58	29.81	2,608,575	2832.33
$NANA_r$	5.23	4.79	3.12	0.89	4.35	2,608,575	2832.33
$R\&D_r$	0.011	0.001	0.02	3.22	26.90	2,608,575	2832.33
ROA_r	-0.007	0.004	0.06	-7.13	237.79	2,608,575	2832.33
LEV_r	0.547	0.514	0.31	5.00	194.38	2,608,575	2832.33
BTM_r	0.664	0.600	0.37	3.35	72.17	2,608,575	2832.33
$RVOLA_r$	0.031	0.029	0.01	2.07	22.76	2,608,575	2832.33
CAR_{mkt}	15.343	-1.109	569.28	2.03	51.31	2,291,080	2487.60
CAR_{ff3}	11.101	-4.143	575.04	1.96	49.48	2,291,080	2487.60
CAR_{ff4}	12.677	-2.851	581.70	1.93	48.65	2,291,080	2487.60
ITR	7.115	1.199	241.51	-0.03	87.99	3,260,242	4684.26
INS	-5.129	-27.297	93.34	10.87	123.51	3,260,242	4684.26

Table 2
Baseline Regressions: Technology Competition and Informed Trading

This table reports the results of baseline regressions. Panel A uses the original variables, while Panel B uses standardized variables in order to facilitate the evaluation of the relative importance among the variables. The sample includes ordinary common stocks (SHRCD = 10 or 11 in CRSP) of (focal) firms listed in the NYSE/AMEX and the NASDAQ over the 921 weeks (18 years) from 1996 to 2013. The dependent variable is Π_b, which is the logit-transform of π_b^w [i.e., $\ln\left(\frac{\pi_b^w}{1-\pi_b^w}\right)$], where π_b^w is the average of daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that bad-news information event occurs (π_b) over three trading days from Tuesday to Thursday within each week. To process order flows used in the above variable, intradaily trades and quotes from 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 based on the Holden and Jacobsen (2014) algorithm from January 2007 to December 2013. The competition-related variables are defined as follows. C_{rmf}: the measure of technology competition (or relative disadvantage in technology) for a focal firm, computed as ($C_r - C_f$), where C_f is the natural logarithm of one plus the number of citations received by a (focal) firm in each week, and C_r is the natural logarithm of one plus the HP-score-weighted average number of citations received in each week by 10 rival firms that have the highest HP-scores [product similarity scores calculated by Hoberg and Phillips (2010, 2016) (HP) on an annual basis and available since 1996]; and P_{rmf}: an alternative measure of technology competition for a focal firm, computed as ($P_r - P_f$), where P_f is the natural logarithm of one plus the number of patents granted to the focal firm in each week, and P_r is the natural logarithm of one plus the HP-score-weighted average number of patents granted in each week to 10 rivals that have the highest HP-scores. Control variables for a focal firm (indicated by subscript '*f*') as well as for its rival firms (indicated by subscript '*r*') (which is obtained as the HP-score-weighted average of the control variables across its 10 rival firms) are defined as follows. *dIH*: the monthly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding; *NANA*: the monthly number of analysts following a firm; *R&D*: the ratio of quarterly research and development expenses (in $million) to quarter-end assets (in $million), and 0 if the expense is missing; *ROA*: the ratio of quarterly net income (in $million) to quarter-end assets (in $million), or 0 if missing; *LEV*: the leverage ratio calculated as ratio of total liabilities to the assets at the quarter-end; *BTM*: the ratio of quarter-end book value (in $million) to quarter-end market capitalization (in $million); and *RVOLA*: the weekly standard deviation of daily stock returns within a week. The values in the first row are estimated coefficients for each explanatory variable, and the values italicized in the second row of each variable are firm-level clustered-error-consistent *t*-statistics. Each regression specification controls for the firm fixed effects and the year-week fixed effects. *AdjR-sqr* is the adjusted R-squared in the regression. *Obs* is the number of observations (firm-weeks) used in the regression. Coefficients significantly different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, ** and *, respectively.

(Table 2: continued)

Panel A: Baseline Regressions, Dep. Var. = Π_b								
Explanat. Var.	(1)		(2)		(3)		(4)	
C_{rmf}	2.942	***	2.715	***	2.423	***	2.108	***
	7.32		*6.62*		*6.05*		*5.25*	
P_{rmf}			1.407	**	1.142	*	0.720	
			2.11		*1.76*		*1.13*	
dIH_f					0.049	*	0.048	*
					1.75		*1.72*	
$NANA_f$					-2.158	***	-2.173	***
					-23.07		*-23.24*	
$R\&D_f$					25.170	***	24.409	***
					3.84		*3.78*	
ROA_f					-0.679		-0.862	
					-0.70		*-0.82*	
LEV_f					3.483	**	2.965	**
					2.33		*2.02*	
BTM_f					0.010		0.009	
					0.60		*0.55*	
$RVOLA_f$					-18.636	***	-12.292	***
					-6.52		*-4.71*	
dIH_r							0.031	
							0.82	
$NANA_r$							0.234	**
							2.29	
$R\&D_r$							74.950	***
							4.99	
ROA_r							1.006	
							0.45	
LEV_r							0.486	
							1.03	
BTM_r							2.390	
							1.57	
$RVOLA_r$							-134.601	***
							-14.70	
Firm Fixed Effect	Yes		Yes		Yes		Yes	
Year-Week Fixed Effect	Yes		Yes		Yes		Yes	
Firm Clustering	Yes		Yes		Yes		Yes	
AdjR-sqr	0.3607		0.3607		0.3678		0.3686	
Obs	2,608,575		2,608,575		2,608,575		2,608,575	

(Table 2: continued)

Panel B: Baseline Regressions with Standardized Variables, Dep. Var. = Π_b								
Explanat. Var.	(1)		(2)		(3)		(4)	
C_{rmf}	0.078	***	0.072	***	0.064	***	0.056	***
	7.32		*6.62*		*6.05*		*5.25*	
P_{rmf}			0.015	**	0.012	*	0.007	
			2.11		*1.76*		*1.13*	
dIH_f					0.004	*	0.004	*
					1.75		*1.72*	
$NANA_f$					-0.567	***	-0.571	***
					-23.07		*-23.24*	
$R\&D_f$					0.043	***	0.042	***
					3.84		*3.78*	
ROA_f					-0.005		-0.006	
					-0.70		*-0.82*	
LEV_f					0.044	**	0.037	**
					2.33		*2.02*	
BTM_f					0.004		0.004	
					0.60		*0.55*	
$RVOLA_f$					-0.028	***	-0.018	***
					-6.52		*-4.71*	
dIH_r							0.002	
							0.82	
$NANA_r$							0.035	**
							2.29	
$R\&D_r$							0.069	***
							4.99	
ROA_r							0.003	
							0.45	
LEV_r							0.010	
							1.03	
BTM_r							0.052	
							1.57	
$RVOLA_r$							-0.116	***
							-14.70	
Firm Fixed Effect	Yes		Yes		Yes		Yes	
Year-Week Fixed Effect	Yes		Yes		Yes		Yes	
Firm Clustering	Yes		Yes		Yes		Yes	
AdjR-sqr	0.3607		0.3607		0.3678		0.3686	
Obs	2,608,575		2,608,575		2,608,575		2,608,575	

Table 3
With Five Rival Firms Only

This table reports the results of regressions, where only five rival firms are used to construct the measures of technology competition. The sample includes ordinary common stocks (SHRCD = 10 or 11 in CRSP) of (focal) firms listed in the NYSE/AMEX and the NASDAQ over the 921 weeks (18 years) from 1996 to 2013. The dependent variable is Π_b, which is the logit-transform of π_b^w [i.e., $\ln\left(\frac{\pi_b^w}{1-\pi_b^w}\right)$], where π_b^w is the average of daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that bad-news information event occurs (π_b) over three trading days from Tuesday to Thursday within each week. To process order flows used in the above variable, intradaily trades and quotes from 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 2013. The competition-related variables are defined as follows. C_{rmf}: the measure of technology competition (or relative disadvantage in technology) for a focal firm, computed as ($C_r - C_f$), where C_f is the natural logarithm of one plus the number of citations received by a (focal) firm in each week, and C_r is the natural logarithm of one plus the HP-score-weighted average number of citations received in each week by five rival firms that have the highest HP-scores [product similarity scores calculated by Hoberg and Phillips (2010, 2016) (HP) on an annual basis and available since 1996]; and P_{rmf}: an alternative measure of technology competition for a focal firm, computed as ($P_r - P_f$), where P_f is the natural logarithm of one plus the number of patents granted to the focal firm in each week, and P_r is the natural logarithm of one plus the HP-score-weighted average number of patents granted in each week to five rivals that have the highest HP-scores. Control variables for a focal firm (indicated by subscript '*f*') as well as for its rival firms (indicated by subscript '*r*') (which is obtained as the HP-score-weighted average of the control variables across its five rival firms) are defined as follows. *dIH*: the monthly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding; *NANA*: the monthly number of analysts following a firm; *R&D*: the ratio of quarterly research and development expenses (in \$million) to quarter-end assets (in \$million), and 0 if the expense is missing; *ROA*: the ratio of quarterly net income (in \$million) to quarter-end assets (in \$million), or 0 if missing; *LEV*: the leverage ratio calculated as ratio of total liabilities to the assets at the quarter-end; *BTM*: the ratio of quarter-end book value (in \$million) to quarter-end market capitalization (in \$million); and *RVOLA*: the weekly standard deviation of daily stock returns within a week. The values in the first row are estimated coefficients for each explanatory variable, and the values italicized in the second row of each variable are firm-level clustered-error-consistent *t*-statistics. Each regression specification controls for the firm fixed effects and the year-week fixed effects. *AdjR-sqr* is the adjusted R-squared in the regression. *Obs* is the number of observations (firm-weeks) used in the regression. Coefficients significantly different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, ** and *, respectively.

(Table 3: continued)

	With 5 Rival Firms: Dep. Var. = Π_b							
Explanat. Var.	(1)		(2)		(3)		(4)	
C_{rmf}	2.294	***	2.095	***	1.838	***	1.666	***
	6.13		*5.50*		*4.94*		*4.44*	
P_{rmf}			1.088	*	0.919		0.682	
			1.70		*1.48*		*1.11*	
dIH_f					0.050	*	0.050	*
					1.77		*1.77*	
$NANA_f$					-2.184	***	-2.184	***
					-23.26		*-23.27*	
$R\&D_f$					25.299	***	25.109	***
					3.91		*3.91*	
ROA_f					-0.675		-0.760	
					-0.69		*-0.76*	
LEV_f					3.394	**	2.983	**
					2.28		*2.03*	
BTM_f					0.010		0.008	
					0.60		*0.51*	
$RVOLA_f$					-18.417	***	-14.560	***
					-6.45		*-5.41*	
dIH_r							0.004	
							0.11	
$NANA_r$							0.121	*
							1.72	
$R\&D_r$							37.112	***
							3.08	
ROA_r							0.542	
							0.38	
LEV_r							0.150	
							0.44	
BTM_r							3.087	***
							6.67	
$RVOLA_r$							-86.642	***
							-13.83	
Firm Fixed Effect	Yes		Yes		Yes		Yes	
Year-Week Fixed Effect	Yes		Yes		Yes		Yes	
Firm Clustering	Yes		Yes		Yes		Yes	
AdjR-sqr	0.3609		0.3609		0.3680		0.3687	
Obs	2,587,925		2,587,925		2,587,925		2,587,925	

Table 4
With Technology Positions Separately for Focal and Rival Firms

This table reports the results of regressions, where the technology positions of focal firms and their rival firms are separately specified. The sample includes ordinary common stocks (SHRCD = 10 or 11 in CRSP) of (focal) firms listed in the NYSE/AMEX and the NASDAQ over the 921 weeks (18 years) from 1996 to 2013. The dependent variable is Π_b, which is the logit-transform of π_b^w [i.e., $\ln\left(\frac{\pi_b^w}{1-\pi_b^w}\right)$], where π_b^w is the average of daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that bad-news information event occurs (π_b) over three trading days from Tuesday to Thursday within each week. To process order flows used in the above variable, intradaily trades and quotes from 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 2013. The technology-related variables are defined as follows. C_f: the natural logarithm of one plus the number of citations received by a (focal) firm in each week; C_r: the natural logarithm of one plus the HP-score-weighted average number of citations received in each week by 10 rival firms that have the highest HP-scores [product similarity scores calculated by Hoberg and Phillips (2010, 2016) (HP) on an annual basis and available since 1996]; P_f : the natural logarithm of one plus the number of patents granted to the focal firm in each week; and P_r: the natural logarithm of one plus the HP-score-weighted average number of patents granted in each week to 10 rivals that have the highest HP-scores. Control variables for a focal firm (indicated by subscript '*f*') as well as for its rival firms (indicated by subscript '*r*') (which is obtained as the HP-score-weighted average of the control variables across its 10 rival firms) are defined as follows. *dIH*: the monthly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding; *NANA*: the monthly number of analysts following a firm; *R&D*: the ratio of quarterly research and development expenses (in $million) to quarter-end assets (in $million), and 0 if the expense is missing; *ROA*: the ratio of quarterly net income (in $million) to quarter-end assets (in $million), or 0 if missing; *LEV*: the leverage ratio calculated as ratio of total liabilities to the assets at the quarter-end; *BTM*: the ratio of quarter-end book value (in $million) to quarter-end market capitalization (in $million); and *RVOLA*: the weekly standard deviation of daily stock returns within a week. The values in the first row are estimated coefficients for each explanatory variable, and the values italicized in the second row of each variable are firm-level clustered-error-consistent *t*-statistics. Each regression specification controls for the firm fixed effects and the year-week fixed effects. *AdjR-sqr* is the adjusted R-squared in the regression. *Obs* is the number of observations (firm-weeks) used in the regression. Coefficients significantly different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, ** and *, respectively.

(Table 4: continued)

With Technology Positions Separately for Focal and Rival Firms: Dep. Var. = Π_b								
Explanat. Var.	(1)		(2)		(3)		(4)	
C_f	-1.158	**	-1.186	**	-1.009	**	-0.996	**
	-2.51		*-2.51*		*-2.21*		*-2.19*	
C_r	7.158	***	6.716	***	5.862	***	5.130	***
	8.35		*7.03*		*6.44*		*5.52*	
P_f			0.248		0.698		0.702	
			0.37		*1.05*		*1.06*	
P_r			1.652		2.659		2.023	
			0.88		*1.47*		*1.13*	
dIH_f					0.049	*	0.049	*
					1.76		*1.73*	
$NANA_f$					-2.156	***	-2.158	***
					-23.17		*-23.14*	
$R\&D_f$					25.409	***	24.590	***
					3.86		*3.80*	
ROA_f					-0.677		-0.845	
					-0.69		*-0.81*	
LEV_f					3.389	**	2.928	**
					2.27		*1.99*	
BTM_f					0.010		0.009	
					0.60		*0.55*	
$RVOLA_f$					-17.721	***	-11.914	***
					-6.26		*-4.57*	
dIH_r							0.030	
							0.81	
$NANA_r$							0.122	
							1.16	
$R\&D_r$							73.287	***
							4.91	
ROA_r							0.724	
							0.33	
LEV_r							0.445	
							0.96	
BTM_r							2.393	
							1.57	
$RVOLA_r$							-129.958	***
							-14.47	
Firm Fixed Effect	Yes		Yes		Yes		Yes	
Year-Week Fixed Effect	Yes		Yes		Yes		Yes	
Firm Clustering	Yes		Yes		Yes		Yes	
AdjR-sqr	0.3610		0.3610		0.3680		0.3688	
Obs	2,608,575		2,608,575		2,608,575		2,608,575	

Table 5
Excluding Self-Citations and Citations Received by Expired Patents

This table reports the results of regressions that use the measures of technology competition constructed with the number of citations but excluding self-citations (in Panel A) and citations received by expired patents (in Panel B). The sample includes ordinary common stocks (SHRCD = 10 or 11 in CRSP) of (focal) firms listed in the NYSE/AMEX and the NASDAQ over the 921 weeks (18 years) from 1996 to 2013. The dependent variable is Π_b, which is the logit-transform of π_b^w [i.e., $\ln\left(\frac{\pi_b^w}{1-\pi_b^w}\right)$], where π_b^w is the average of daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that bad-news information event occurs (π_b) over three trading days from Tuesday to Thursday within each week. To process order flows used in the above variable, intradaily trades and quotes from 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 2013. The competition-related variables are defined as follows. C_{rmf}: the measure of technology competition (or relative disadvantage in technology) for a focal firm, computed as ($C_r - C_f$), where C_f is the natural logarithm of one plus the number of citations received by a (focal) firm (excluding self-citations or citations received by expired patents) in each week, and C_r is the natural logarithm of one plus the HP-score-weighted average number of citations received (excluding self-citations or citations received by expired patents) in each week by 10 rival firms that have the highest HP-scores [product similarity scores calculated by Hoberg and Phillips (2010, 2016) (HP) on an annual basis and available since 1996]; and P_{rmf}: an alternative measure of technology competition for a focal firm, computed as ($P_r - P_f$), where P_f is the natural logarithm of one plus the number of patents granted to the focal firm in each week, and P_r is the natural logarithm of one plus the HP-score-weighted average number of patents granted in each week to 10 rivals that have the highest HP-scores. Control variables for a focal firm (indicated by subscript '*f*') as well as for its rival firms (indicated by subscript '*r*') (which is obtained as the HP-score-weighted average of the control variables across its 10 rival firms) are defined as follows. *dIH*: the monthly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding; *NANA*: the monthly number of analysts following a firm; *R&D*: the ratio of quarterly research and development expenses (in $million) to quarter-end assets (in $million), and 0 if the expense is missing; *ROA*: the ratio of quarterly net income (in $million) to quarter-end assets (in $million), or 0 if missing; *LEV*: the leverage ratio calculated as ratio of total liabilities to the assets at the quarter-end; *BTM*: the ratio of quarter-end book value (in $million) to quarter-end market capitalization (in $million); and *RVOLA*: the weekly standard deviation of daily stock returns within a week. The values in the first row are estimated coefficients for each explanatory variable, and the values italicized in the second row of each variable are firm-level clustered-error-consistent *t*-statistics. Each regression specification controls for the firm fixed effects and the year-week fixed effects. *AdjR-sqr* is the adjusted R-squared in the regression. *Obs* is the number of observations (firm-weeks) used in the regression. Coefficients significantly different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, ** and *, respectively.

(Table 5: continued)

Panel A: Excluding Self-Citations, Dep. Var. = Π_b								
Explanat. Var.	(1)		(2)		(3)		(4)	
C_{rmf}	3.001	***	2.780	***	2.496	***	2.145	***
	7.04		*6.67*		*6.14*		*5.27*	
P_{rmf}			2.360	***	1.987	***	1.475	**
			3.66		*3.19*		*2.41*	
dIH_f					0.049	*	0.048	*
					1.75		*1.73*	
$NANA_f$					-2.158	***	-2.172	***
					-23.07		*-23.24*	
$R\&D_f$					25.172	***	24.413	***
					3.84		*3.79*	
ROA_f					-0.679		-0.862	
					-0.70		*-0.82*	
LEV_f					3.480	**	2.964	**
					2.33		*2.02*	
BTM_f					0.010		0.009	
					0.60		*0.55*	
$RVOLA_f$					-18.604	***	-12.280	***
					-6.51		*-4.70*	
dIH_r							0.031	
							0.82	
$NANA_r$							0.228	**
							2.23	
$R\&D_r$							74.889	***
							4.99	
ROA_r							1.002	
							0.45	
LEV_r							0.484	
							1.03	
BTM_r							2.387	
							1.57	
$RVOLA_r$							-134.491	***
							-14.70	
Firm Fixed Effect	Yes		Yes		Yes		Yes	
Year-Week Fixed Effect	Yes		Yes		Yes		Yes	
Firm Clustering	Yes		Yes		Yes		Yes	
AdjR-sqr	0.3607		0.3607		0.3678		0.3686	
Obs	2,608,575		2,608,575		2,608,575		2,608,575	

(Table 5: continued)

Panel B: Excluding Citations Received by Expired Patents, Dep. Var. = Π_b								
Explanat. Var.	(1)		(2)		(3)		(4)	
C_{rmf}	2.655	***	2.374	***	2.070	***	1.761	***
	6.34		*5.54*		*4.95*		*4.20*	
P_{rmf}			1.685	**	1.426	**	0.980	
			2.51		*2.18*		*1.53*	
dIH_f					0.049	*	0.048	*
					1.75		*1.73*	
$NANA_f$					-2.159	***	-2.175	***
					-23.08		*-23.27*	
$R\&D_f$					25.228	***	24.463	***
					3.84		*3.79*	
ROA_f					-0.677		-0.862	
					-0.69		*-0.82*	
LEV_f					3.477	**	2.956	**
					2.33		*2.01*	
BTM_f					0.010		0.009	
					0.60		*0.55*	
$RVOLA_f$					-18.671	***	-12.295	***
					-6.53		*-4.71*	
dIH_r							0.031	
							0.82	
$NANA_r$							0.245	**
							2.40	
$R\&D_r$							75.190	***
							5.00	
ROA_r							1.037	
							0.46	
LEV_r							0.490	
							1.04	
BTM_r							2.390	
							1.57	
$RVOLA_r$							-134.895	***
							-14.73	
Firm Fixed Effect	Yes		Yes		Yes		Yes	
Year-Week Fixed Effect	Yes		Yes		Yes		Yes	
Firm Clustering	Yes		Yes		Yes		Yes	
AdjR-sqr	0.3607		0.3607		0.3677		0.3686	
Obs	2,608,575		2,608,575		2,608,575		2,608,575	

Table 6

A Base-Case Analysis: OLS Regressions with the Competition Measure Constructed with Citations Made by Patent Applicants

This table reports the results of OLS regressions that use the measures of technology competition constructed with citations made by patent applicants, as a base-case analysis for 2SLS regressions. The sample includes ordinary common stocks (SHRCD = 10 or 11 in CRSP) of (focal) firms listed in the NYSE/AMEX and the NASDAQ over the 921 weeks (18 years) from 1996 to 2013. The dependent variable is Π_b, which is the logit-transform of π_b^w [i.e., $\ln\left(\frac{\pi_b^w}{1-\pi_b^w}\right)$], where π_b^w is the average of daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that bad-news information event occurs (π_b) over three trading days from Tuesday to Thursday within each week. To process order flows used in the above variable, intradaily trades and quotes from 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 2013. The competition-related variables are defined as follows. C_{rmf}^{app}: the measure of technology competition (or relative disadvantage in technology) for a focal firm, computed as ($C_r^{app} - C_f^{app}$), where C_f^{app} is the natural logarithm of one plus the number of citations made by the patent applicant in a (focal) firm in each week, and C_r^{app} is the natural logarithm of one plus the HP-score-weighted average number of citations made by the patent applicants in 10 rival firms that have the highest HP-scores [product similarity scores calculated by Hoberg and Phillips (2010, 2016) (HP) on an annual basis and available since 1996]; and P_{rmf}: an alternative measure of technology competition for a focal firm, computed as ($P_r - P_f$), where P_f is the natural logarithm of one plus the number of patents granted to the focal firm in each week, and P_r is the natural logarithm of one plus the HP-score-weighted average number of patents granted in each week to 10 rivals that have the highest HP-scores. Control variables for a focal firm (indicated by subscript '*f*') as well as for its rival firms (indicated by subscript '*r*') (which is obtained as the HP-score-weighted average of the control variables across its 10 rival firms) are defined as follows. *dIH*: the monthly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding; *NANA*: the monthly number of analysts following a firm; *R&D*: the ratio of quarterly research and development expenses (in $million) to quarter-end assets (in $million), and 0 if the expense is missing; *ROA*: the ratio of quarterly net income (in $million) to quarter-end assets (in $million), or 0 if missing; *LEV*: the leverage ratio calculated as ratio of total liabilities to the assets at the quarter-end; *BTM*: the ratio of quarter-end book value (in $million) to quarter-end market capitalization (in $million); and *RVOLA*: the weekly standard deviation of daily stock returns within a week. The values in the first row are estimated coefficients for each explanatory variable, and the values italicized in the second row of each variable are firm-level clustered-error-consistent *t*-statistics. Each regression specification controls for the firm fixed effects and the year-week fixed effects. *AdjR-sqr* is the adjusted R-squared in the regression. *Obs* is the number of observations (firm-weeks) used in the regression. Coefficients significantly different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, ** and *, respectively.

(Table 6: continued)

A Base-Case Analysis: Using the Measure Constructed with Citations Made by Patent Applicants, Dep. Var. = Π_b								
Explanat. Var.	(1)		(2)		(3)		(4)	
C_{rmf}^{app}	1.896	***	1.804	***	1.329	***	0.984	**
	4.85		*4.52*		*3.48*		*2.56*	
P_{rmf}			0.600		0.296		-0.272	
			0.83		*0.44*		*-0.41*	
dIH_f					-0.013		-0.014	
					-0.31		*-0.31*	
$NANA_f$					-2.475	***	-2.523	***
					-22.96		*-23.59*	
$R\&D_f$					19.543	**	19.192	**
					2.27		*2.23*	
ROA_f					-3.943		-4.338	
					-1.28		*-1.38*	
LEV_f					1.239		0.843	
					0.61		*0.41*	
BTM_f					-0.003		-0.003	
					-0.77		*-0.64*	
$RVOLA_f$					9.258	***	13.296	***
					2.65		*3.89*	
dIH_r							0.099	
							1.38	
$NANA_r$							0.380	***
							3.45	
$R\&D_r$							65.313	***
							3.22	
ROA_r							7.973	***
							2.77	
LEV_r							1.292	***
							2.99	
BTM_r							-0.177	
							-0.33	
$RVOLA_r$							-79.977	***
							-7.16	
Firm Fixed Effect	Yes		Yes		Yes		Yes	
Year-Week Fixed Effect	Yes		Yes		Yes		Yes	
Firm Clustering	Yes		Yes		Yes		Yes	
AdjR-sqr	0.3704		0.3704		0.3758		0.3761	
Obs	1,563,357		1,563,357		1,563,357		1,563,357	

Table 7
Two-Stage Least Squares (2SLS) Regressions with an Instrumental Variable

This table reports the results of two-stage least squares (2SLS) regressions, where the measure of technology competition constructed with citations made by the examiner at the USPTO is used as an instrumental variable (IV). The sample includes ordinary common stocks (SHRCD = 10 or 11 in CRSP) of (focal) firms listed in the NYSE/AMEX and the NASDAQ over the 624 weeks (12 years) from 2002 to 2013. The dependent variable in the 2nd stage is Π_b, which is the logit-transform of π_b^w [i.e., $\ln\left(\frac{\pi_b^w}{1-\pi_b^w}\right)$], where π_b^w is the average of daily posterior probability (conditional on observing the number of daily buyer- and seller-initiated trades) that bad-news information event occurs (π_b) over three trading days from Tuesday to Thursday within each week. To process order flows used in the above variable, intradaily trades and quotes from 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 2013. The competition-related variables are defined as follows. C_{rmf}^{app}: the measure of technology competition for a focal firm, computed as ($C_r^{app} - C_f^{app}$), where C_f^{app} is the natural logarithm of one plus the number of citations made by the patent applicant in a (focal) firm in each week, and C_r^{app} is the natural logarithm of one plus the HP-score-weighted average number of citations made by the patent applicants in 10 rival firms that have the highest HP-scores [product similarity scores calculated by Hoberg and Phillips (2010, 2016) (HP) on an annual basis and available since 1996]; C_{rmf}^{exa}: the instrumental variable (IV), which is the measure of technology competition for a focal firm, computed as ($C_r^{exa} - C_f^{exa}$), where C_f^{exa} is the natural logarithm of one plus the number of citations made by the patent examiner at the USPTO in each week, and C_r^{app} is the natural logarithm of one plus the HP-score-weighted average number of citations made by the patent examiner for 10 rival firms that have the highest HP-scores; *Fitted*_C_{rmf}^{app}: the predicted value of C_{rmf}^{app} in the 1st-stage regression of C_{rmf}^{app} on C_{rmf}^{exa} and other control variables; and P_{rmf}: an alternative measure of technology competition for a focal firm, computed as ($P_r - P_f$), where P_f is the natural logarithm of one plus the number of patents granted to the focal firm in each week, and P_r is the natural logarithm of one plus the HP-score-weighted average number of patents granted in each week to 10 rivals that have the highest HP-scores. Control variables for a focal firm (indicated by subscript '*f*') as well as for its rival firms (indicated by subscript '*r*') (which is obtained as the HP-score-weighted average of the control variables across its 10 rival firms) are defined as follows. *dIH*: the monthly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding; *NANA*: the monthly number of analysts following a firm; *R&D*: the ratio of quarterly research and development expenses (in $million) to quarter-end assets (in $million), and 0 if the expense is missing; *ROA*: the ratio of quarterly net income (in $million) to quarter-end assets (in $million), or 0 if missing; *LEV*: the leverage ratio calculated as ratio of total liabilities to the assets at the quarter-end; *BTM*: the ratio of quarter-end book value (in $million) to quarter-end market capitalization (in $million); and *RVOLA*: the weekly standard deviation of daily stock returns within a week. The values in the first row are estimated coefficients for each explanatory variable, and the values italicized in the second row of each variable are firm-level clustered-error-consistent *t*-statistics. Each regression specification controls for the firm fixed effects and the year-week fixed effects. *AdjR-sqr* is the adjusted R-squared in the regression. *Obs* is the number of observations (firm-weeks) used in the regression. Coefficients significantly different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, ** and *, respectively. In the lower part of the table, the Kleibergen-Paap *rk LM*-statistic (*Kleibergen-Paap Stat*) for an under-identification test (and *p*-values in italic) is reported. The null hypothesis for the under-identification test is "the IV cannot explain endogenous explanatory variable," and the rejection of the null hypothesis indicates that the IV can significantly explain the endogenous variable (and thus is relevant).

(Table 7: continued)

	(1)		(2)		(3)		(4)	
	C_{rmf}^{app}	Π_b	C_{rmf}^{app}	Π_b	C_{rmf}^{app}	Π_b	C_{rmf}^{app}	Π_b
2SLS Regressions with an Instrumental Variable								
Fitted_C_{rmf}^{app}		5.118 ***		4.075 ***		3.059 ***		2.318 **
		5.26		*3.67*		*-2.84*		*2.10*
C_{rmf}^{exa}	0.484 ***		0.380 ***		0.380 ***		0.373 ***	
	46.82		*38.85*		*39.13*		*39.10*	
P_{rmf}			0.826 ***	4.008 *	0.825 ***	4.493 **	0.776 ***	2.945
			37.38	*1.90*	*37.33*	*2.23*	*34.49*	*1.48*
dIH_f					0.000	-0.013	0.000	-0.014
					1.42	*-0.30*	*1.26*	*-0.32*
$NANA_f$					-0.004 ***	-2.464 ***	-0.005 ***	-2.504 ***
					-4.88	*-22.81*	*-6.30*	*-23.40*
$R\&D_f$					0.005	19.330 **	0.004	19.100 **
					0.09	*2.25*	*0.08*	*2.23*
ROA_f					-0.010	-3.963	-0.012	-4.323
					-1.10	*-1.29*	*-1.25*	*-1.38*
LEV_f					-0.005	1.217	-0.008	0.867
					-0.36	*0.60*	*-0.65*	*0.43*
BTM_f					0.000	-0.003	0.000	-0.003
					0.08	*-0.76*	*1.15*	*-0.64*
$RVOLA_f$					0.002	9.566 ***	0.023 *	13.320 ***
					0.14	*2.73*	*1.67*	*3.90*
dIH_r							0.001 ***	0.098
							2.63	*1.36*
$NANA_r$							0.010 ***	0.320 ***
							12.86	*2.83*
$R\&D_r$							0.383 ***	63.350 ***
							2.78	*3.13*
ROA_r							0.064 ***	7.696 ***
							3.62	*2.68*
LEV_r							0.006 ***	1.261 ***
							2.67	*2.92*
BTM_r							-0.002	-0.174
							-1.34	*-0.32*
$RVOLA_r$							-0.320 ***	-78.330 ***
							-5.71	*7.03*
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AdjR-sqr	0.6586	0.3701	0.6736	0.3703	0.6739	0.3758	0.6750	0.3761
Obs	1,563,357	1,563,357	1,563,357	1,563,357	1,563,357	1,563,357	1,563,357	1,563,357
Kleibergen-Paap Stat	593.42		575.52		577.31		584.62	
p-value	*0.00*		*0.00*		*0.00*		*0.00*	

Table 8
Return Predictability of Technology Competition

This table reports the regression results for the return predictability of technology competition. The sample includes ordinary common stocks (SHRCD = 10 or 11 in CRSP) of (focal) firms listed in the NYSE/AMEX and the NASDAQ over the 921 weeks (18 years) from 1996 to 2013. The dependent variable is the 3-day cumulative abnormal return (CAR), which is adjusted for one, three, or four factors. To compute factor (*F*)-adjusted cumulative abnormal returns (CARs) (in basis points) over three trading days from Tuesday to Thursday within each week, for each of the three days (day *d*), a factor beta(s) and the intercept are first estimated from the time-series regression of the daily excess return (the raw return minus the one-month T-bill rate) on the (one, three, or four) factor(s) over the window from day *d*-260 to day *d*-11. With the estimated $\hat{\beta}$'s available, the daily abnormal return (AR) for day *d* is obtained as AR = the daily excess return - $\sum_{k=1}^{K}\hat{\beta}_k F_k$. Then a CAR is the sum of ARs over the three trading days (Tuesday-Thursday). CARs used in Panels A-C are defined as follows. CAR_{mkt}: CAR adjusted for the market factor (MKT = $R_m - R_f$); CAR_{ff3}: CAR adjusted for the Fama-French (1993) three factors (MKT, SMB, and HML); and CAR_{ff4}: CAR adjusted for the Fama-French (1993) three factors (MKT, SMB, and HML) and the Carhart (1997) momentum factor (UMD). The competition-related variables are defined as follows. C_{rmf}: the measure of technology competition (or relative disadvantage in technology) for a focal firm, computed as $(C_r - C_f)$, where C_f is the natural logarithm of one plus the number of citations received by a (focal) firm in each week, and C_r is the natural logarithm of one plus the HP-score-weighted average number of citations received in each week by 10 rival firms that have the highest HP-scores [product similarity scores calculated by Hoberg and Phillips (2010, 2016) (HP) on an annual basis and available since 1996]; and P_{rmf}: an alternative measure of technology competition for a focal firm, computed as $(P_r - P_f)$, where P_f is the natural logarithm of one plus the number of patents granted to the focal firm in each week, and P_r is the natural logarithm of one plus the HP-score-weighted average number of patents granted in each week to 10 rivals that have the highest HP-scores. Control variables for a focal firm (indicated by subscript '*f*') as well as for its rival firms (indicated by subscript '*r*') (which is obtained as the HP-score-weighted average of the control variables across its 10 rival firms) are defined as follows. *dIH*: the monthly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding; *NANA*: the monthly number of analysts following a firm; *R&D*: the ratio of quarterly research and development expenses (in $million) to quarter-end assets (in $million), and 0 if the expense is missing; *ROA*: the ratio of quarterly net income (in $million) to quarter-end assets (in $million), or 0 if missing; *LEV*: the leverage ratio calculated as ratio of total liabilities to the assets at the quarter-end; *BTM*: the ratio of quarter-end book value (in $million) to quarter-end market capitalization (in $million); and *RVOLA*: the weekly standard deviation of daily stock returns within a week. The values in the first row are estimated coefficients for each explanatory variable, and the values italicized in the second row of each variable are firm-level clustered-error-consistent *t*-statistics. Each regression specification controls for the firm fixed effects and the year-week fixed effects. *AdjR-sqr* is the adjusted R-squared in the regression. *Obs* is the number of observations (firm-weeks) used in the regression. Coefficients significantly different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, ** and *, respectively.

(Table 8: continued)

Return Predictability of Technology Competition						
	Panel A: Dep. Var. = CAR_{mkt}		Panel B: Dep. Var. = CAR_{ff3}		Panel C: Dep. Var. = CAR_{ff4}	
Explanat. Var.	(1)	(2)	(3)	(4)	(5)	(6)
C_{rmf}	-3.318***	-2.752***	-2.904***	-2.332**	-2.860***	-2.405**
	-3.30	*-2.73*	*-2.82*	*-2.26*	*-2.70*	*-2.26*
P_{rmf}	-1.086	0.122	-3.294	-2.034	-2.929	-2.037
	-0.29	*0.03*	*-0.86*	*-0.53*	*-0.74*	*-0.51*
dIH_f	0.352	0.356	0.367	0.371	0.367	0.371
	1.16	*1.18*	*1.18*	*1.20*	*1.14*	*1.15*
$NANA_f$	-1.388***	-1.324***	-1.417***	-1.341***	-1.480***	-1.413***
	-10.93	*-10.36*	*-10.86*	*-10.26*	*-11.16*	*-10.65*
$R\&D_f$	109.847**	103.225**	114.523**	107.197**	117.499**	109.915**
	2.33	*2.23*	*2.54*	*2.43*	*2.52*	*2.41*
ROA_f	75.581***	75.877***	72.046***	72.218***	72.932***	73.071***
	3.65	*3.65*	*3.60*	*3.61*	*3.47*	*3.48*
LEV_f	34.474***	35.141***	32.140***	32.790***	32.567***	33.104***
	5.84	*5.89*	*5.89*	*5.95*	*6.19*	*6.24*
BTM_f	23.552***	23.279***	21.292***	21.068***	19.965***	19.796***
	14.81	*14.65*	*13.30*	*13.17*	*12.21*	*12.10*
$RVOLA_f$	344.379***	327.936***	343.314***	328.734***	300.507***	290.229***
	4.26	*3.99*	*4.26*	*4.00*	*3.69*	*3.50*
dIH_r		-0.131		-0.409		-0.334
		-0.36		*-1.10*		*-0.87*
$NANA_r$		-0.363*		-0.450**		-0.384**
		-1.93		*-2.35*		*-1.98*
$R\&D_r$		281.172***		323.957***		348.162***
		3.39		*3.46*		*3.70*
ROA_r		-0.309		2.751		-3.044
		-0.03		*0.29*		*-0.30*
LEV_r		1.379		1.180		1.105
		0.97		*0.93*		*0.72*
BTM_r		0.211		-0.021		-0.040
		1.25		*-0.13*		*-0.25*
$RVOLA_r$		270.513***		237.008***		161.751***
		4.75		*4.11*		*2.72*
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes	Yes	Yes	Yes
AdjR-sqr	0.0224	0.0224	0.0099	0.0100	0.0070	0.0071
Obs	2,291,080	2,291,080	2,291,080	2,291,080	2,291,080	2,291,080

Table 9

Technology Competition and Institutional Investors' Trading Activities

This table reports the results of regressions, where weekly net selling of a (focal) firm's shares by an institutional investor is regressed on the firm's measure of technology competition. The sample includes ordinary common stocks (SHRCD = 10 or 11 in CRSP) of (focal) firms listed in the NYSE/AMEX and the NASDAQ over the 696 weeks (14 years) from 1997 to 2010. The dependent variable is *INS*, which is each institutional investor's weekly net selling (in %) of shares in a given focal firm from Tuesday to Thursday, calculated (using ANcerno) as the dollar volume sold by each institution minus the dollar volume bought by the same institution in a firm, scaled by the sum of the two values. The competition-related variables are defined as follows. C_{rmf}: the measure of technology competition (or relative disadvantage in technology) for a focal firm, computed as ($C_r - C_f$), where C_f is the natural logarithm of one plus the number of citations received by a (focal) firm in each week, and C_r is the natural logarithm of one plus the HP-score-weighted average number of citations received in each week by 10 rival firms that have the highest HP-scores [product similarity scores calculated by Hoberg and Phillips (2010, 2016) (HP) on an annual basis and available since 1996]; and P_{rmf}: an alternative measure of technology competition for a focal firm, computed as ($P_r - P_f$), where P_f is the natural logarithm of one plus the number of patents granted to the focal firm in each week, and P_r is the natural logarithm of one plus the HP-score-weighted average number of patents granted in each week to 10 rivals that have the highest HP-scores. Control variables for a focal firm (indicated by subscript '*f*') as well as for its rival firms (indicated by subscript '*r*') (which is obtained as the HP-score-weighted average of the control variables across its 10 rival firms) are defined as follows. *dIH*: the monthly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding; *NANA*: the monthly number of analysts following a firm; *R&D*: the ratio of quarterly research and development expenses (in $million) to quarter-end assets (in $million), and 0 if the expense is missing; *ROA*: the ratio of quarterly net income (in $million) to quarter-end assets (in $million), or 0 if missing; *LEV*: the leverage ratio calculated as ratio of total liabilities to the assets at the quarter-end; *BTM*: the ratio of quarter-end book value (in $million) to quarter-end market capitalization (in $million); and *RVOLA*: the weekly standard deviation of daily stock returns within a week. The values in the first row are estimated coefficients for each explanatory variable, and the values italicized in the second row of each variable are firm- and institution-level clustered-error-consistent *t*-statistics. Each regression specification controls for the firm fixed effects, the year-week fixed effects and institutional fixed effects. *AdjR-sqr* is the adjusted R-squared in the regression. *Obs* is the number of observations (institution-firm-weeks) used in the regression. Coefficients significantly different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, ** and *, respectively.

(Table 9: continued)

Institutional Investors' Trading Activities: Dep. Var. = *INS*								
Explanat. Var.	(1)		(2)		(3)		(4)	
C_{rmf}	0.844	**	0.762	**	0.882	**	0.786	**
	2.22		*1.98*		*2.36*		*2.16*	
P_{rmf}			0.416		0.335		0.208	
			1.25		*1.04*		*0.64*	
dIH_f					-0.001		-0.002	
					-0.02		*-0.04*	
$NANA_f$					0.289	***	0.245	***
					3.85		*3.61*	
$R\&D_f$					-32.591	***	-33.223	***
					-3.70		*-3.78*	
ROA_f					-12.635	**	-13.147	***
					-2.47		*-2.60*	
LEV_f					-1.462		-1.790	
					-0.66		*-0.80*	
BTM_f					-0.030		-0.031	
					-0.72		*-0.74*	
$RVOLA_f$					40.659	**	44.656	***
					2.29		*4.33*	
dIH_r							0.062	
							0.75	
$NANA_r$							0.279	***
							2.93	
$R\&D_r$							15.274	
							0.93	
ROA_r							4.636	
							1.32	
LEV_r							0.219	
							0.51	
BTM_r							0.053	
							1.45	
$RVOLA_r$							-4.643	
							-0.19	
Firm Fixed Effect	Yes		Yes		Yes		Yes	
Year-Week Fixed Effect	Yes		Yes		Yes		Yes	
Institution fixed effect	Yes		Yes		Yes		Yes	
Firm Clustering	Yes		Yes		Yes		Yes	
Institution Clustering	Yes		Yes		Yes		Yes	
AdjR-sqr	0.0470		0.0470		0.0472		0.0473	
Obs	3,260,242		3,260,242		3,260,242		3,260,242	

Table 10
Profitability of Institutional Investors' Trading on the Information about Technology Competition

This table reports the results of regressions, where institutional investors' trading return is regressed on the measure of technology competition, institutional investor's net selling of the firm's shares, and their interaction term. The sample includes ordinary common stocks (SHRCD = 10 or 11 in CRSP) of (focal) firms listed in the NYSE/AMEX and the NASDAQ over the 696 weeks (14 years) from 1997 to 2010. The dependent variable is *ITR*, which is each institutional investor's trading return (in basis points) from trading shares in a given focal firm over the Tuesday-Thursday period (calculated using the ANcerno database from 1997 to 2010), for which a cumulative stock return based on the execution price and the Thursday close price is first obtained for each trade made by an institutional investor, and then the principal-weighted average return is computed across all trades made by the same institution from Tuesday to Thursday within a week. Institutional trading and competition-related variables are defined as follows. *INS*: each institutional investor's weekly net selling (in %) of shares in a given focal firm from Tuesday to Thursday, calculated (using ANcerno) as the dollar volume sold by each institution minus the dollar volume bought by the same institution in a firm, scaled by the sum of the two values; H_C: a dummy variable set at 1 if C_{rmf} is in the 90th percentile and 0 otherwise, where C_{rmf} the measure of technology competition (or relative disadvantage in technology) for a focal firm, computed as $(C_r - C_f)$, where C_f is the natural logarithm of one plus the number of citations received by a (focal) firm in each week, and C_r is the natural logarithm of one plus the HP-score-weighted average number of citations received in each week by 10 rival firms that have the highest HP-scores [product similarity scores calculated by Hoberg and Phillips (2010, 2016) (HP) on an annual basis and available since 1996]; $INS*H_C$: the interaction term between *INS* and H_C; and P_{rmf}: an alternative measure of technology competition for a focal firm, computed as $(P_r - P_f)$, where P_f is the natural logarithm of one plus the number of patents granted to the focal firm in each week, and P_r is the natural logarithm of one plus the HP-score-weighted average number of patents granted in each week to 10 rivals that have the highest HP-scores. Control variables for a focal firm (indicated by subscript '*f*') as well as for its rival firms (indicated by subscript '*r*') (which is obtained as the HP-score-weighted average of the control variables across its 10 rival firms) are defined as follows. *dIH*: the monthly change in the fraction of the total (direct and indirect) insider holdings (IH) relative to the number of shares outstanding; *NANA*: the monthly number of analysts following a firm; *R&D*: the ratio of quarterly research and development expenses (in $million) to quarter-end assets (in $million), and 0 if the expense is missing; *ROA*: the ratio of quarterly net income (in $million) to quarter-end assets (in $million), or 0 if missing; *LEV*: the leverage ratio calculated as ratio of total liabilities to the assets at the quarter-end; *BTM*: the ratio of quarter-end book value (in $million) to quarter-end market capitalization (in $million); and *RVOLA*: the weekly standard deviation of daily stock returns within a week. The values in the first row are estimated coefficients for each explanatory variable, and the values italicized in the second row of each variable are firm-level clustered-error-consistent *t*-statistics. Each regression specification controls for the firm fixed effects, the year-week fixed effects and institutional fixed effects. *AdjR-sqr* is the adjusted R-squared in the regression. *Obs* is the number of observations (institution-firm-weeks) used in the regression. Coefficients significantly different from zero at the significance levels of 1%, 5%, and 10% are indicated by ***, ** and *, respectively.

(Table 10: continued)

Profitability of Institutional Investors' Trading Activities: Dep. Var. = *ITR*								
Explanat. Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
INS	-0.078***	-0.081***	-0.078***	-0.081***	-0.078***	-0.081***	-0.078***	-0.081***
	-9.01	*-8.88*	*-9.00*	*-8.88*	*-9.01*	*-8.89*	*-9.01*	*-8.89*
H_C	-0.498	-0.545	-0.118	-0.162	-0.113	-0.156	-0.048	-0.091
	-0.37	*-0.40*	*-0.09*	*-0.12*	*-0.08*	*-0.11*	*-0.03*	*-0.07*
INS*H_C		0.037***		0.037***		0.038***		0.037***
		3.08		*3.08*		*3.09*		*3.08*
P_{rmf}			-0.968	-0.977	-0.810	-0.819	-0.801	-0.810
			-1.48	*-1.50*	*-1.26*	*-1.28*	*-1.24*	*-1.26*
dIH_f					0.120	0.120	0.121	0.121
					0.77	*0.77*	*0.78*	*0.78*
$NANA_f$					-0.205***	-0.204***	-0.205***	-0.204***
					-2.71	*-2.70*	*-2.70*	*-2.70*
$R\&D_f$					25.558	25.405	23.062	22.923
					1.16	*1.16*	*1.04*	*1.04*
ROA_f					-17.541	-17.628	-17.281	-17.367
					-1.49	*-1.50*	*-1.47*	*-1.48*
LEV_f					0.465	0.459	0.768	0.763
					0.16	*0.15*	*0.26*	*0.25*
BTM_f					0.060	0.060	0.061	0.061
					1.02	*1.01*	*1.02*	*1.02*
$RVOLA_f$					74.528**	74.622**	68.960**	69.053**
					2.37	*2.37*	*2.20*	*2.20*
dIH_r							0.083	0.085
							0.42	*0.43*
$NANA_r$							0.061	0.060
							0.67	*0.66*
$R\&D_r$							59.204**	58.853**
							1.97	*1.96*
ROA_r							-0.742	-0.748
							-0.20	*-0.20*
LEV_r							-0.635	-0.636
							-1.31	*-1.31*
BTM_r							-0.004	-0.004
							-0.19	*-0.18*
$RVOLA_r$							33.869	33.835
							1.02	*1.02*
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institution Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institution Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AdjR-sqr	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143
Obs	3,260,242	3,260,242	3,260,242	3,260,242	3,260,242	3,260,242	3,260,242	3,260,242