Market Manipulation and Innovation

Douglas Cumming
DeSantis Distinguished Professor of Finance and Entrepreneurship
College of Business, Florida Atlantic University
777 Glades Road
Boca Raton, Florida 33432 USA
cummingd@fau.edu

Shan Ji
Capital Markets CRC Limited (CMCRC)
3/55 Harrington St, Sydney,
NSW 2000, Australia
sji@cmcrc.com

Rejo Peter
York University -- Schulich School of Business
4700 Keele Street, Toronto,
Ontario M3J 1P3, Canada
rpeter12@schulich.yorku.ca

Monika Tarsalewska
University of Exeter Business School
XFI building, Streatham Campus,
Rennes Drive, Exeter EX4 4ST, UK
m.tarsalewska@exeter.ac.uk

This Draft: December 2, 2019

Acknowledgments: We owe thanks to the seminar participants at the Canadian Law and Economics Association, Financial Management Association, Miami University, SKEMA Business School, Steven's Institute of Technology, University of Ottawa, University of Toronto, and University of Chile, Santiago. All errors are our own. Douglas Cumming gratefully acknowledges the Social Science Research and Humanities Council of Canada for financial support. Rejo Peter gratefully acknowledges the support of Capital Markets CRC (CMCRC) and Michael Aitken for the opportunity to visit CMCRC throughout 2015 to work on this project.

Market Manipulation and Innovation

Abstract

End-of-day price manipulation is associated with short-termism of the firm's orientation, long-term harm to a firm's equity values, and commensurate with reduced incentives for employees to innovate. Insider trading, by contrast, enables innovators to achieve exacerbated profits from innovation. Using a sample of suspected manipulation events based on intra-day data for all stocks from nine countries over eight years, we find evidence consistent with these real impacts of market manipulation on innovation. These findings are not attributable to "bad" firms innovating less and manipulating more, since the average firm subjected to manipulation in the sample is more innovative during the pre-manipulation period.

Keywords: Market Manipulation, End-of-Day Dislocation, Insider Trading, Patents, Innovation, Intellectual Property Rights, Law and Finance

JEL Classification: G14; G18; O30

"***The stock-price manipulation*** involved in massive buybacks—and the resulting exorbitant executive pay—are thus not just moral or legal problems. The consequences… net disinvestment, loss of shareholder value, ***diminished investment in innovation***, destruction of jobs, exploitation of workers, ***windfall gains for activist insiders***, rapidly increasing inequality and sustained economic stagnation." -- Forbes[1]

1. Introduction

Financial market misconduct comes in a variety of forms. Two of the most commonly observed (and, therefore, commonly studied) forms of manipulation include insider trading (Allen and Gale, 1992; Allen and Gorton, 1992; Meulbrook, 1992; Bebchuk and Fershtman, 1994; Agrawal and Cooper, 2015; Bernilie et al., 2015; Aitken et al., 2015b) and end-of-day manipulation (Atanasov et al., 2015; Aitken et al., 2015a). It is well known that when there is information only known by insiders, they can trade in advance of public dissemination of the information for short-term profit at the expense of the counterparties in the trade and at the expense of the long-term value to the firm. It is perhaps somewhat less well known that there are massive incentives to manipulate closing price by ramping up end-of-day trading to push the closing price to an artificially high level. End-of-day prices are used to determine the expiration value of derivative instruments and directors' options, determine the price of seasoned equity issues, evaluate broker performance, compute net asset values of mutual funds, and compute stock indices (Aitken et al., 2015).[2]

In theory, there are different perspectives on whether or not market manipulation should enhance or mitigate innovation. On one hand, the presence of market manipulation is associated with short-termism of the firm's orientation, which is inconsistent with a long-term managerial focus on innovation. Over- or under-valuation of a firm's equity causes agency problems (Jensen, 2005; Marciukaityte and Varma, 2008), and in turn agency problems impede innovation

[1] Steven Denning, 2017, "Resisting The Lure Of Short-Termism: Kill 'The World's Dumbest Idea'" in Forbes https://www.forbes.com/sites/stevedenning/2017/01/08/resisting-the-lure-of-short-termism-how-to-achieve-long-term-growth/#26c739101ca0

[2] See also Aggarwal and Wu (2006); Allen and Gale (1992); Allen and Gorton (1992); Allen et al. (2006), Comerton-Forde and Putnins (2014) Merrick et al. (2005); O'Hara (2001); O'Hara and Mendiola (2003); Peng and Röell (2013); Pirrong (1999, 2004); and Röell (1993).

(Manso, 2011). Also, market manipulation imposes long-term harm to a firm's equity values and commensurate reduced incentives for employees to innovate. Ferreira et al. (2014) find that public firms have fewer incentives when exploring radical new innovations, because the rapid incorporation of good news into market prices creates incentives for short-termist behavior. Bereskin et al. (2018) find that firms engaging in managerial manipulation of R&D expenditures have reduced levels of firm innovation. Market manipulation may be yet another reason for why public firms innovate less and have more incentives for short-termist behavior. On the other hand, manipulation may enhance the gains to insiders from innovation, which would, in turn, increase the incentives for managers to innovate. The link between market manipulation and innovation is ambiguous in theory, and one must, therefore, look to data to ascertain the validity of the connection between manipulation and innovation.

In this paper, we empirically study the link between market manipulation and innovation by assembling a sample of 131,129 firm-year observations across nine countries (Australia, Canada, China, India, Japan, New Zealand, Singapore, Sweden, and the United States) spanning the years 2003-2010. It is widely regarded that insider trading is hard to prove, as trading before information announcements may be attributable to market anticipation. Similarly, end-of-day dislocation may not always be attributable to manipulation and, instead, arise through unusual volatility and end-of-day market activity. Our empirical measures of insider trading and end-of-day manipulation are based on surveillance data of suspected insider trading and suspected end-of-day dislocation derived from alerts (computer algorithms that send messages to surveillance authorities). The advantages of these measures are that they avoid delays in enforcement, and they are uniform without bias from differences in enforcement across firms and countries and over time. Also, suspected problems with a firm can be as equally harmful to a firm as litigated problems, regarding focusing management on short-termism, hurting equity values, and diverting attention away from innovative activities.

The data examined in this paper indicate that end-of-day dislocation mitigates patents, and we argue that this evidence is consistent with the notion that manipulation is associated with short-termism of the firm's orientation, long-term harm to a firm's equity values, and commensurate with reduced incentives for employees to innovate. The economic significance of

this effect is greater when dislocation occurs on days when dislocation is more likely to be attributable to manipulation, such as at the end of the month, quarter, and/or year. The data indicate that end-of-day dislocation has a pronounced negative impact on patenting, even after controlling for other market efficiency variables such as liquidity, among other factors. The economic significance is such that the presence of end-of-day dislocation mitigates a subsequent year's patenting by 7.3%. Estimated differently, a 1-standard deviation increase in the number of dislocation events in one year is associated with a 1.9% reduction in patenting during the subsequent year.

In contrast to the negative impact of dislocation on patents, information leakage has no effect on low-quality patents, but it does have a positive impact on high-quality patents. The intuition behind this result is that insiders make use of superior information to profit from innovation. It is very similar in spirit to evidence from Agrawal and Cooper (2015) and Atanasov et al. (2015) who show that insider trading around times of scandal and market manipulation is common and used to enhance profits to insiders. In particular, we find that the economic significance is such that the presence of information leakage cases increases a subsequent year's patent citations by 5.1%. Estimated differently, a 1-standard deviation increase in the number of information leakage cases in one year is associated with a 1.65 % increase in patent citations in the subsequent year. Interestingly, the strong positive association between insider trading and patents is only observed in non-crisis times and for high-quality patents. The intuition is that at any given time there exists the negative impact of misconduct on innovation due to short-termism and poor managerial focus. For information leakage, however, there is a counter force of insiders profiting more. In bad economic times, the ability to illegally profit as an insider is reduced, and the risk of being caught is greater, because regulators are especially diligent in crisis periods. Overall, the effect of short-termism associated with information leakage is stronger than the latter effect of expected profits during crisis periods.

One possible concern with the connection between innovation and manipulation is that "bad" firms are more likely to be associated with manipulation, and "bad" firms are less likely to innovate. If this is the case, a finding that firms with manipulated stock prices patent less is not particularly surprising, because both are symptomatic of firms being bad-type firms; put

differently, the effect may be a selection effect versus a treatment effect. We can rule out this explanation at the outset, since, in our sample, we observe that in the period prior to end-of-day manipulation, firms that are manipulated have 0.43 patents on average, compared to 0.39 patents for those that do not face end-of-day manipulation. Similarly, in the period prior to information leakage, firms that have information leakage have 0.95 patents on average, compared to 0.35 patents for those without information leakage. Therefore, the data do not support a connection between manipulation and innovation due to a third unobservable "bad quality" variable. We provide a variety of propensity score matching techniques and other checks to examine the change in patents from the pre-manipulation to post-manipulation period to establish a causal connection between manipulation and innovation and explicitly show the treatment estimates (Table 10, below).

The link between market manipulation and patenting brings into focus related literatures – market microstructure, financial misconduct and regulation, and innovation. To this end, there are two papers that are most closely related to ours. First, Levine et al. (2015) examine whether or not insider trading enforcement affects subsequent innovation, and they find a strong positive link, based on a sample of 94 countries from 1976 to 2006. Second, Fang et al. (2014) show that there is a negative relationship between liquidity and innovation due to increased exposure to hostile takeovers and a higher presence of institutional investors who do not actively gather information or monitor. Fan et al.'s evidence is taken from a sample of U.S. firms over from 1994 to 2005.

Our analyses, however, are distinct from these papers in a number of important ways. First, in Levine et al. (2015), the sample covers a period where there is variation in whether or not insider trading laws were enforced, and the enforcement of insider trading laws is the central variable of interest. By contrast, in our more recent sample, there is no variation in whether or not inside trading laws were enforced, but there is variation in enforcement pertaining to a broader set of ways in which stocks may be manipulated. We find such variation to have a positive effect on manipulation, consistent with Levine et al.

Second, we examine whether or not there were actual events of apparent manipulation based on alerts (computer algorithms) examining historical microstructure data. To this end, our paper is distinct from the Fang et al. study, which relates liquidity to innovation; also, their study does not examine whether or not a stock was manipulated, such as through insider trading or end-of-day manipulation. Unlike Fang et al., the literature surprisingly shows a negative relation between patenting and liquidity; we observe a robust and significantly positive effect of liquidity on patenting, including in the U.S. subsample, and we apply the same patent data source, as in prior papers, but for more recent years. This new finding suggests that the relation between liquidity and patenting is not stable over time. Our data indicate that the positive effect of liquidity on innovation, however, is mitigated by the presence of end-of-day dislocation, which implies that more nuanced market microstructure relationships explain innovation more (or better?) than previously documented.

The data examined herein also confirm the importance of country-level factors that affect innovation, such as intellectual property rights across countries that encourage patenting, and firm-specific variables like age and capital expenditures. Our findings are robust to numerous robustness checks, such as including/excluding the U.S. during financial crisis years, patent applications versus patent grants, different liquidity deciles, propensity score matching analyses, and difference-in-differences tests for firms with and without dislocation, among other factors.

Our evidence has a number of important policy implications. Manipulation is common, and there are significant expenditures across countries to detect securities fraud (Jackson and Roe, 2009). Our evidence suggests that there are significant externalities to manipulation, including a marked reduction in innovation. In view of these externalities, our findings imply that expenditures on the enforcement of securities regulations around the world may be more important than previously considered.

This paper is organized as follows: Section 2 discusses the economic link between market manipulation and innovation. Section 3 presents the data. Section 4 provides univariate tests of the relation between market manipulation and patents. Multivariate analyses are presented in Section 5. Limitations and extensions are discussed in Section 6. The final section offers

concluding remarks. Additional robustness tests are provided in the Appendices as well as in an accompanying Online Appendix.

2. Economic Link between Market Manipulation and Innovation

Nearly without exception, financial market misconduct is viewed as being very costly to financial markets and, thus, is an active area of scholarly study (Kyle and Viswanathan, 2008). Research on the consequences of financial market misconduct can be categorized into four types of papers: (1) managerial consequences, such as salaries, termination, and jail terms (Karpoff et al., 2008a; Bereskin et al., 2014; Aharony et al., 2015); (2) stock market participation at the country level (La Porta at el., 1997, 1998, 2002, 2006) and individual level (Giannetti and Wang, 2016); (3) consequences in term funds under management, such as for hedge funds (Bollen and Pool, 2009; Gerken and Dimmock, 2012, 2016) and mutual funds (Chapman et al., 2013); and (4) share price declines and legal penalties (Karpoff et al., 2008b; Karpoff and Lou, 2010; Vismara et al., 2015). In this paper, we extend this line of literature by examining a fifth category not previously studied: the effect of financial market misconduct on innovation.

Table 1 summarizes the economic causal link between market manipulation market, in a microstructure sense, and innovation. At first glance, the link between market microstructure an innovation, normally two very distinct fields, may seem unusual, but there is a stream of literature that connects market liquidity to innovation (e.g., Fang et al., 2014); therefore, this paper is not the first to make the connection. The innovation here is to change the analysis of liquidity (e.g., bid-ask spreads) and instead focus on market manipulation. Arguably, as manipulation and fraud can have substantial consequences for a firm with respect to a firm's long-term economic outcomes (Karpoff et al., 2008a,b, 2012), it is natural to focus on market manipulation and not see the other microstructure properties of a firm's stock, such as its liquidity. It is widely regarded that governance affects innovation (Ayyagari et al., 2011, 2014; O'Connor and Rafferty 2012; Chen et al., 2014; Lyandres and Palazzo, 2016; Yung, 2016), and here, we are extending the governance impact to an analysis of market misconduct.

[TABLE 1 ABOUT HERE]

As discussed in the introduction, here we consider the two most common types of manipulation: 1) end-of-day manipulation (defined by massive share price movements during the last 15 minutes of trading one day and a reversal the next morning), and 2) information leakage (defined by massive share price movements prior to news announcements). These manipulation events are measured in the year prior to the innovation year and pertain to manipulations that were not caused by the announcement of the innovation outcome, but were, instead, in reference to other firm events.

Table 1 consists of two panels: Panel A lists the first-order effects connecting manipulation to innovation. Over- or under-valuation of a firm's equity gives rise to severe agency problems insofar as managers have short-term pressures to manipulate information released to the public to justify the improper valuation (Jensen, 2005; Marciukaityte and Varma, 2008), and in turn there agency problems and short-term perspectives impede innovation (Manso, 2011). Manipulation damages long-term equity values (Aggarwal and Wu, 2006; Karpoff et al., 2008a,b; Agrawal and Cooper, 2015; Aitken et al., 2015a,b). The reduced long-term prospects for a firm worsen its ability to raise future equity (Brown et al., 2009, 2013) and shift the focus of a firm's management to short-termism and short-term pay structures (Peng and Röell, 2014). The short-term focus of the firm is inconsistent with long-term innovation outcomes, as innovation requires a long-term horizon (Manso, 2011) and incentive pay (Shen and Zhang, 2017). Therefore, in general, we expect manipulation -- such as that of end-of-day manipulation -- to negatively impact innovation. As well, we note that it does not matter who is actually responsible for the end-of-day manipulation in terms of either insiders or outsiders, as the effects summarized in Table 1 all point in the same direction that it will have a negative impact on a firm's innovation.

There is a caveat with respect to the impact of information leakage and insider trading on innovation that is distinct from end-of-day manipulation and innovation. Specifically, insiders may take advantage of the knowledge of innovation and trade in advance of the announcement of an innovation (see also Agrawal and Cooper, 2015; Levine, 2015). The ability of insiders to profit off of the inside knowledge of an innovation announcement may lead to exacerbated

profits for insiders and inspire a firm with wrongdoers as insiders to pursue more innovation. If this effect outweighs the other effects, it is possible that a firm with frequent and pronounced information leakage has more innovation.

Our two hypotheses are, therefore, as follows:

Hypothesis 1: *End-of-day manipulation lowers innovation in subsequent years.*

Hypothesis 2: *Information leakage raises innovation in subsequent years if the effect of insider profits outweighs other effects.*

Table 1, Panel B lists three second-order effects. First, stock price informativeness is a second-order effect insofar as end-of-day manipulation (insider trading) lowers (raises) stock price informativeness which, in turn, reduces (raises) information leakage to competing firms and thereby reduces (increases) incentives for firms to invest in innovation (see the model of Ding, 2015, for complete details). Second, both end-of-day price manipulation and insider trading reduce liquidity, in line with the close connection between manipulation, price accuracy, and liquidity proposed by Kyle and Viswanathan (2008). A reduction in liquidity, in turn, may have a positive effect on innovation, if mergers are thereby less likely (Fang et al., 2014); conversely, a reduction in liquidity may have a negative effect on innovation if the ability to raise future capital is lower (Brown et al., 2009, 2013). Third, firms with pronounced end-of-day dislocation and information leakage may be less likely to be the subject of mergers, which, in turn, reduces the possibility of takeovers and, hence, reduces the likelihood of employee layoffs, thereby increasing the incentives of employees to innovate (Fang et al., 2014). While these and possible other second-order effects may exist in practice, they are not expected to dominate the first-order effects summarized above.

We test the two hypotheses summarized above and listed in Table 1, below.

3. Data and Variable Construction

3.1 Sample Selection and Data Sources

This study covers 11 stock exchanges from nine countries from 2003 to 2010. The sample includes Australia (the Australian Securities Exchange [ASX]), Canada (the TSX Venture Exchange [TSXV]), China (the Shanghai Stock Exchange [SSE]), India (the Bombay Stock Exchange [BSE] and the National Stock Exchange of India Ltd. [NSE]), Japan (the Tokyo Stock Exchange [TSE]), New Zealand (the New Zealand Stock Exchange [NZX]), Singapore (the Singapore Exchange Ltd. [SGX]), Sweden (the Stockholm Stock Exchange [STO]) and the United States (the Nasdaq Stock Market [NASDAQ] and the New York Stock Exchange [NYSE]). Table 2 provides the definition and source of variables used in the study.

[TABLE 2 ABOUT HERE]

Patent data is obtained from the EPO's Worldwide Patent Statistical Database (PATSTAT), which includes patent data on 90 million patent documents from over 100 patent offices around the world. The PATSTAT database is published biannually, and we use the 2014 Autumn edition. The database provides information regarding the first publication and grant dates, citation links, technological classifications, and applicant and inventor identifications for each patent application. The patent data is augmented using the ECOOM-EUROSTAT-EPO PATSTAT Person Augmented Table (EEE-PPAT), which provides sector codes and harmonized company names for each of the patent applications (Plessis et al., 2009; Magerman et al., 2009; Peeters et al., 2009). The manipulation data is obtained from SMARTS Group Inc. and the Capital Markets Cooperative Research Centre (CMCRC). SMARTS Group Inc. provides market surveillance products to over 40 stock exchanges around the world. Firm-level data is obtained from Datastream.

3.2 Measuring Innovation

In the study, we used two measures of patenting activity: 1) the number of patent applications made by a firm in a year, and 2) the number of citations received by these patents. The number of patent applications is a measure of the quantity or productivity of innovation, while the number of citations received is a measure of the relative importance or quality of innovation.

We use the logarithm of one plus the number of patent applications in the year t+1, INNOV_PAT(t+1), as the main dependent variable in the study. We use the logarithm of the number of patents, because the patent data are right skewed with the 75th percentile of the number of patents equal to zero. We add one to the number of patents before taking the logarithm to ensure that we don't have missing values for firms with 0 patents. We use the application date of patents instead of the grant date, because the application date is closer to the actual date of innovation.

The second measure of innovation, INNOV_CITE(t+1), is the natural logarithm of one plus the number of citations received for patents filed in the year t+1. The number of citations received has been adjusted for truncation bias, based on the methodology developed by Hall et al. (2001, 2005). We implemented the following procedure to adjust for the truncation bias in citations: (1) For each cohort of patents applied for between 1991 and 2002, we obtain the citation lag of the patents using 12 years of actual citation data. To illustrate, for patents applied in 1991 (Cohort 1), we measure the number of citations received in each year from 1991 (citation lag of 0) to 2002 (citation lag of 11). Similarly, for patents applied for in 2002 (Cohort 12), we measure the number of citations received in each year from 2002 (citation lag of 0) to 2013 (citation lag of 11). (2) For each major IPC technology classification of patents, k, in each of the cohorts, we obtain the citation lag distribution, W, as the proportion of citations received with lags of 0 to 11 years with the total number of citations received. Subsequently, we compute the cumulative share of citations received with lags of 0 to 11 within each technology classification of patents. We average the cumulative share of citations across the 12 cohorts. (3) Finally, for

patent citations received between 2003 and 2010, we divide the actual citations received by the average cumulative share of citations and use the formula:

$$Adjusted\ citations_t^k = \frac{Unadjusted\ citations_t^k}{\sum_{s=0}^{2013-t} W_{sk}},$$

where W_{sk} is the average share of citations received with lag s, within technology classification k.

As part of robustness checks, we also used two alternative measures for the number of patent applications: 1) the number of patents applied for and eventually granted (INNOV_PAT_GRNT), and 2) the number of patents applied for and eventually granted, adjusted for truncation bias (INNOV_PAT_GRNT_ADJ). Using only patent applications that have been eventually granted introduces truncation bias, because there is a lag between patent application and the grant date of the patent. We correct for this truncation bias by using the grant lag distribution, based on the methodology of Hall, Jaffe, and Trajtenberg (2001, 2005). We compute the grant lag distribution for patents filed and granted between 1991 and 2002. The truncation-adjusted patents are then computed using:

$$Adjusted\ patents = \frac{Unadjusted\ Patents}{\sum_{s=0}^{2014-t} W_s},$$

where W_s is the application-grant lag distribution computed as the percentage of patents applied for in any year that has been granted in s year.

Using patents as a measure of innovation has its disadvantages. By using the number of patents, we ignore differences between industries with regard to the intensity and duration of patents. We control for this by including industry- and firm-level controls for patent data. Using the number of patent applications also ignores how efficient the firms are at converting their innovative inputs (R&D expenditures and intangible inputs) to innovative outputs.

3.3 Measuring Manipulation

We use two measures of manipulation: 1) end-of-day price dislocation (EOD), and 2) information leakage (infoleakage) alerts computed by the CMCRC and SMARTS surveillance staff.

An EOD price alert is created by looking at the price change between the last trade price (P_t) and last available trade price 15 minutes before the continuous trading period ends (P_{t-15}). For securities exchanges that have a closing auction, the close price at auction is used ($P_{auction}$). A price movement is dislocated if it is four standard deviations away from the mean price change during the benchmark period for the past 100 trading days. To be considered as a case of EOD price dislocation, at least 50% of the price dislocation has to revert at open on the next trading day. Hence, the price movement between the last trade price (P_t) and the next day's opening price (P_{t+1}), and between the last trade price (P_t) and last available trade price 15 minutes before the continuous trading period ends (P_{t-15}), has to be more than 50%. $(P_{auction \text{ or } t} - P_{t+1})/(P_{auction \text{ or } t} - P_{t-15}) \geq 50\%$.

To measure the information leakage alert, CMCRC and SMARTS first examine all news releases from the exchanges themselves. CMCRC and SMARTS measure the return to security from the six days prior to the announcement to the two days after the announcement. They double check the Thompson Reuters News Network to ensure that they did not miss any important news announcements. They consider only news events that have no companion news announcements that could explain price movements in the six days before and the two days after the relevant announcement that could explain the price movement. For each news announcement, a price movement is abnormal if it is three standard deviations away from the mean abnormal return during the 250-day benchmarking period ending 10 days before the news release. To be included in our sample, the stock must have at least 150 days' worth of trading activities. A one-factor market model based on the market index for each exchange is used to calculate daily abnormal returns. To be included in the final data set as a suspected information leakage case, the CAR around each event over the period [t-6, t+2] must be three standard deviations away from the normal nine-day CAR for each individual stock. Once the suspected information

leakage case is defined, the abnormal profit per case is calculated to include both the trading volume and multiple abnormal returns from six days before to the day before the news announcement. SMARTS surveillance staff independently examines the data to distinguish between market anticipation and suspected insider trading; since SMARTS includes as insider trading only large movements that are three-standard-deviation changes, the possibility that insider trades could be viewed as market anticipation is mitigated.

3.4 Measuring Control Variables

The main control variables used in the study were obtained from Datastream. The control variables are measured at the end of the fiscal year t. We control for the profitability of the firm using the return on assets, ROA(t), measured as the income before extraordinary items divided by the book value of total assets. Asset tangibility, PPETA(t), is measured as the property, plant, and equipment expenditure divided by the book value of total assets. Leverage, LEV(t), is measured as the book value of debt divided by the book value of total assets. Investment in fixed assets, CAPEXTA(t), is measured as capital expenditures scaled by the book value of total assets. Firm age, LN_FIRM_AGE(t), is measured as a natural logarithm of one plus the firm *i*'s age, approximated by the number of years listed on Datastream. Liquidity of the firm, Liquidity(t), is computed as the natural logarithm of the inverse of the AMIHUD measure of illiquidity. AMIHUD is computed as follows:

$$A_{ij} = \frac{1}{D_{iy}} \sum_{i=1}^{D_{iy}} \frac{|r_{it}|}{Dvol_{it}},$$

where A_{iy} is the AMIHUD measure of firm i in year y. R_{it} and $Dvol_{it}$ are the daily return and daily dollar trading volume for stock i on day t. D_{iy} is the number of days with available ratio in year y. A higher AMIHUD value indicates a higher level of illiquidity. Hence, we use the logarithm of the inverse of AMIHUD as the measure of liquidity. We have considered other variables such as price informativeness (Ding, 2015; Mathers et al., 2017) and other law and finance variables pertaining to creditor rights (La Porta et al., 1998), among other things, but did not find any material differences in the results reported herein. Other specifications are available on request.

The summary statistics of the main variables used in the study are provided in Table 3.

[TABLE 3 ABOUT HERE]

4. Univariate Tests

Table 4 presents univariate comparison of means tests and shows the comparison of the percentage change in patent applications [patent citations] for firms that experienced manipulation versus those that have not experienced end-of-day dislocation or information leakage over the period from t-1 to t+1, where t is the year in which there was manipulation. The non-manipulation sample in Table 4 is any firm-year observation where the EOD dummy or the information leakage dummy is equal to zero. Panel A shows the results for patent application. Panel B shows the results for patent citations. We separate the tests into regimes with high versus low intellectual property rights (where 5 is the cutoff, to account for very weak legal environments).

The data indicate that prior to dislocation events, firms in low IPR environments that have experienced dislocation have significantly less pronounced changes in patent applications [patent citations] by -0.24%[0.57%] relative to those that have not experienced dislocation events where the change was 4.57% [4.46%], and these differences are statistically significant at the 1% level, consistent with Hypothesis 1. These differences are not statistically significant for firms in high IPR environments.

[TABLE 4 ABOUT HERE]

Table 4 also presents the univariate comparison tests for firms that have and have not experienced information leakage events. The data indicate that firms in low IPR environments that have experienced information leakage have a greater percentage increase, at 8.65%, in patent applications than those that have not, at 2.99%, and these differences are significant at the 1% level, consistent with Hypothesis 2; however, there is not a significant difference in patent citations among these firms in low IPR environments. Firms in high IPR environments that have

experienced information leakage have a greater percentage increase, at 4.25% [21.89%], in patent applications [patent citations] than those that have not, at 0.43% [6.18%], and these differences are significant at the 1% level.

Overall, the univariate tests are consistent with Hypothesis 1, that the impact of dislocation on patents is strongly negative and statistically significant, and this effect is particularly strong in low IPR regimes. However, the impact of information leakage on patents is strongly positive and significant, consistent with Hypothesis 2, and this effect is significant in both low and high IPR regimes. These effects are depicted graphically in Figures 1, 2.A and 2.B.

[FIGURES 1 AND 2 ABOUT HERE]

To complement the univariate statistics, in Figure 1.A we present end-of-day dislocation and percentage changes in subsequent year patent applications by industry sector. The data indicate that for 8 of 11 sectors (not including oil and gas, banks, and software and computer services), there were higher levels of innovation among non-end-of-day dislocation firms. These differences were statistically significant for technology hardware and equipment, mining, industrial engineering, pharmaceuticals and biotechnology (consistent with other work linking capital markets to market intelligence such as Markovitch, Steckel and Young, 2005), and software and computer services, at the 10% level, and insignificant in the other industries. Overall, the evidence in Figure 3.A strongly supports Hypothesis 1.

[FIGURES 3.A and 3.B ABOUT HERE]

Figure 3.B presents information leakage and percentage changes in subsequent year patent applications by sector. The data indicate that innovation was higher in every sector in the year after information leakage except for in the area of financial services, and the differences were statistically significant for mining (1%), chemicals (5%), technology hardware and equipment (5%), and electronic and electrical equipment (10%). Overall, the evidence in Figure 3.B strongly supports Hypothesis 2.

5. Multivariate Tests

5.1. Base Model Specifications

Tables 4 and 5 present the baseline regression estimates with pooled OLS and random effects, respectively.[3] Table 6 differs from Table 5 in that the use of random effects enables the inclusion of country-level institutional indices that do not vary over time. The results from the three regression models in Table 5 and five regression models in Table 6 are quite consistent and not sensitive to the inclusions of different sets of right-hand-side variables.

[TABLES 4 AND 5 ABOUT HERE]

Tables 4 and 5 indicate that the end-of-day dummy variable for the first year, in which there was dislocation, is statistically insignificant in all of the specifications, but the end-of-day subsequent dummy variable is negative and significant at least at the 5% level of significance in all of the specifications, consistent with Hypothesis 1. The economic significance is such that firms that have experienced end-of-day dislocation have lower patents by 3.5% in the most conservative estimate (Table 6, Panel A, Model 3), and by 7.7% in the least conservative estimate (Table 6, Panel A, Model 4). Similarly, following end-of-day dislocation, firms lower their citations by 15.4% in the most conservative estimate (Table 6, Panel B, Model 5) and by 25.1% in the least conservative estimate (Table 6, Panel B, Model 1). As an alternative specification, in which we use a count of the number of dislocation cases (Table 5, Model 2 and Table 6, Model 2), we see that a 1-standard deviation increase in the number of dislocation cases is associated with a 1.5% reduction in the number of patents in the most conservative estimate (Table 5, Panel A, Model 2) and a 1.9% reduction in the number of patents in the least conservative estimate (Table 6, Panel A, Model 2). Similarly, a 1-standard deviation increase in the number of dislocation cases is associated with a 5.9% reduction (Table 5, Panel B, Model 2)

[3] In addition to the Pooled OLS and Random Effects model, we used a Poisson model with the number of patent applications and the number of patent citations as the main dependent variable. We find similar results using either firm fixed effects or industry fixed effects Poisson models.

in the number of citations in the least conservative estimate and a 6.4% reduction in the number of citations in the least conservative estimate (Table 6, Panel B, Model 2)

A 1-standard deviation increase in liquidity is associated with a 46% increase in the number of patents and a 78.6% increase in the number of citations in the subsequent period (Table 6, Model 1 and Models 2-5 are very similar). This finding is in contrast to the Fang et al. (2014) results in the U.S., but that study was based on a U.S.-only sample from an earlier time period, 1994-2005, while our sample is based on nine countries from 2003 to 2010. In Appendix A, we study the U.S.-only sample from 2003 to 2005 and the same data as Feng et al. (2014) and find results consistent with Tables 4 and 5 with a positive effect of liquidity on innovation. Also, these results indicate that the relation between liquidity and patenting is perhaps not completely stable over time. Also, Fang at al. do not examine whether or not a stock was manipulated, such as through insider trading or end-of-day manipulation. Appendix B performs further robustness tests of the relation between liquidity and innovation with propensity score matched analyses, and shows a consistent and positive effect of liquidity on innovation for 3 out of four tests: nearest-neighbor matching for the change in the number of patents, four-nearest-neighbor matching for the change in the number of patents, and four-nearest-neighbor matching for the change in the natural log of the number of patents; the nearest-neighbor matching for the change in the number of patents without logs shows a positive but statistically insignificant effect of liquidity on patents.

Further, Table 6, Panel A (Panel B), Model 5 shows that the interaction between liquidity and end-of-day dislocation is statistically significant at the 1% level, and the positive association between liquidity and the number of patents (number of citations) is less pronounced by 8.7% (26.4%) for firms that have experienced end-of-day dislocation. These new findings in Tables 4 and 5 indicate that the positive effect of liquidity on innovation is mitigated by the presence of end-of-day dislocation. Overall, the data indicate that the relation between liquidity and innovation may be more nuanced by other market microstructure factors, and the changes in microstructure factors over time could account for at least part of the changes in the relation between liquidity and innovation over time.

Some of the other control variables in Tables 4 and 5 are significant in ways that we might expect. Most notably, a 1-standard deviation increase in the IPR index is associated with a 47.8% increase in the number of patents (Table 6, Panel A, Models 4 and 5) and a 66% increase in the number of citations in the subsequent period (Table 6, Panel B, Models 4 and 5), which is consistent with a large amount of literature documenting the importance of IPR in spurring innovation (e.g., Branstetter et al., 2006; Blind, 2012). As a related matter, at the country level, a 1-standard deviation increase in the Enforcement Index (La Porta et al., 1998) is associated with a 56.1% increase in the number of patents (Table 6, Panel A, Model 3) and a 50.5% increase in the number of citations in the subsequent period (Table 6, Panel B, Model 3).

Some of the firm-specific control variables are statistically significant as well. The data indicate that a 1-standard deviation increase in ROA is associated with a 2.3% decrease in the number of patents in the subsequent period (Table 6, Model 1 and Models 2-5 are similar). A 1-standard deviation increase in leverage is associated with a 2.2% increase in the number of patents in the subsequent period (Table 6, Model 4, but this effect is insignificant in Models 1 and 2). A 1-standard deviation increase in capital expenditures over assets is associated with a 2.1% decrease in the number of patents in the subsequent period (Table 6, Model 1 and Models 2-5 are similar). A 1-standard deviation increase in market/book is associated with a 2.5% decrease in the number of patents in the subsequent period (Table 6, Model 1 and Models 2-5 are similar). And, finally, a 1-standard deviation increase in the natural logarithm of the firm's age is associated with a 47.5% increase in the number of patents in the subsequent period (Table 6, Model 1 and Models 2-5 are similar).

5.2. Robustness Checks

The remaining regression tables and appendices present further robustness checks to account for other subsamples of the data, measurement issues, endogeneity, and regression model specifications, which are as follows. To maintain conciseness, we present only the results considering the number of patents, INNOV_PAT, as the main dependent variable. Table 7, Panel A, Model 1 shows the results with the non-US subsample, and the data and results are consistent with the full-sample results reported in Table 5 and Table 6, with the economic significance of

EOD manipulation slightly more pronounced. Model 2 excludes the global financial crisis period from August 2007 to December 2008, and the findings are consistent. Model 3 includes the global financial crisis period only, and the impact of EOD manipulation on patents is stronger (almost twice as large as the non-financial crisis period). Models 4, 5, and 6 show a negative effect of EOD manipulation on patents for the subset of applied and granted patents, including adjustments for truncation bias, and winsorizing, respectively.

The information leakage variable for suspected insider trading is negative and statistically significant in Table 7, Model 3 for the crisis years only, consistent with Levine et al. (2015) that insider trading is a detriment to innovation. But these results are not stable for information leakage in Models 4 and 5 in Table 7, Panel A, which shows a positive and significant effect for applied and granted patents, and applied and granted patents adjusted for truncation bias, consistent with Hypothesis 2. These results imply that insiders have a pronounced incentive to encourage innovation if they can engage in insider trading and reap exacerbated benefits from such innovation. In particular, we find that the economic significance is such that the presence of information leakage increases a subsequent year's patent citation from 5.1% (Table 5, Panel B, Model 2) to 6.4% (Table 5, Panel B, Model 1). Also, the economic significance is such that the presence of leakage cases increases a subsequent year's patent citation by 5.1%. Estimated differently, a 1-standard deviation increase in the number of information leakage cases in one year is associated with a 1.65 % increase in patent citations in the subsequent year (Table 5, Panel B, Model 2). This effect is slightly different in magnitude in Table 6, Panel B for patents that have been applied for and granted and adjusted for truncation bias; the presence of information leakage increases a subsequent year's patents from 5.16% (Model 1) to 5.19% (Model 2). Table 6, Panel B, Model 3 shows that the economic significance is such that the presence of information leakage increases a subsequent year's patents applied for and granted by 6.51%.

Table 7, Panel B shows robustness to different patent measures (adjusted applied and granted in Models 1 and 2, and applied and granted in Model 3), and citations per patent (Model 4). Table 7, Panel C shows stability of the negative effect of EOD manipulation on patenting for different types of clustering (Petersen, 2009) and by industry-year and country-year in Models 1

and 2, respectively. Models 3 and 4 show similar stability of this main result with different winsorizing at 2.5%/97.5%, and 5%/95%, respectively.

The other control variables in Table 7, Panels A, B and C are statistically significant in ways that are consistent with the results in Tables 4 and 5. Liquidity and the Intellectual Property Rights Index are positively and significantly related to liquidity at the 1% level in all of Models 1-6. Likewise, the other firm-specific variables are consistent with the findings reported earlier.

[TABLE 7 ABOUT HERE]

Table 8 shows the results for different liquidity deciles. The data indicate that EOD manipulation has a strong, statistically significant negative effect on innovation in Models 1 and 2 for the top 10th and 20th liquidity deciles, but not the bottom 80th and 90th deciles in Models 3 and 4, respectively. The other control variables, including liquidity, are significant in ways indicated above for Models 1 and 2. However, in Models 3 and 4, the other control variables are largely insignificant, except for the IPR index and Liquidity in Model 3.

Unlike EOD manipulation, information leakage has a statistically insignificant negative effect on innovation in Models 1 and 2 for the top 10th and 20th liquidity deciles, and a strong and statistically significant effect on innovation for the bottom 80th and 90th deciles, respectively.

In short, for the most liquid stocks, EOD manipulation is harmful to innovation, consistent with Hypothesis 1, while liquidity helps promote innovation. For the least liquid stocks, by contrast, insider trading has a pronounced negative effect on innovation, and this effect is the only relevant factor for the bottom liquidity decile.

[TABLE 8 ABOUT HERE]

Table 9 shows the results for the days on which EOD dislocation is more likely to be associated with manipulation, namely the end-of-the-month days, where manipulators have a

pronounced incentive to push up the price for reasons of compensation and option expiration. The data indicate that the effect of EOD manipulation is stronger when end-of-month days are considered. Also, the data shows that the impact of EOD manipulation is statistically significant regardless of whether or not the other manipulation days are included in or excluded from the sample.

[TABLE 9 ABOUT HERE]

Table 10 reports the results with propensity score matching. The first step regressions show factors that are connected to more frequent EOD manipulation and information leakage. Note that the two alternative specifications with and without the liquidity variable affect the sign and significance of lagged patenting on EOD manipulation and information leakage. As mentioned in the introduction, on average, firms with more innovation are more likely to be associated with manipulation, and, similarly, firms with higher liquidity have more innovation (see Appendix A). The alternative first-stage specifications, however, do not affect the second-stage regressions. In the second step regressions, the data show a consistent and negative effect of EOD manipulation on innovation for four out of four tests in Models 1 and 2: nearest-neighbor matching for the change in the number of patents (with and without logs), and four-nearest-neighbor matching for the change in the number of patents (with and without logs). For the information leakage results in Table 10, the effect is insignificant for the change in the number of patents in Model 3, but negative and significant for the change in the natural log of the number of patents in Model 4.

[TABLE 10 ABOUT HERE]

Also, we considered 2SLS tests of the impact of EOD manipulation and information leakage on innovation. One instrument we had used was the lagged patents in the industry, with the intuition that some industries may be subjected to different levels of manipulation. Another instrument we had used was lagged manipulation at the industry level, with the intuition that firms in some industries consistently experience more manipulation over time. We recognize that neither of these instruments is ideal, as they don't perfectly satisfy the exclusion restriction.

Nevertheless, the statistical and economic significance of the second-stage results for the effect of EOD patents are not materially affected by the specification of the first-stage model. The economic significance in the second-stage estimate for EOD manipulation on patents is stronger with the use of different instruments than without. Alternative specifications not presented here but are available on request.

6. Limitations and Extensions

This paper focuses on two types of manipulation: 1) EOD manipulation and information leakage, and 2) suspected insider trading. There are many other types of manipulation, such as wash trades, option backdating, and accounting fraud, among others (see Cumming et al., 2015, for a survey). We are unable to ascertain these different types of manipulation in this sample for each of the countries and years in the data. Future research with different data could shed more light on the question of whether other types of manipulation have a stronger impact on manipulation.

This paper focuses on nine countries (Australia, Canada, China, India, Japan, New Zealand, Singapore, Sweden, and the United States) from 2003 to 2010. We show that the sensitivity of prior results on liquidity and innovation depends on the time period chosen. While we show the robustness of our results to different subsets of the data by country and time period, future research may very well uncover new insights with different and more expansive data.

7. Conclusion

This paper studied the impact of suspected market manipulation, including end-of-day manipulation and insider trading around information leakage events, on the number of patents and the number of citations, based on a sample of nine countries spanning the years 2003-2010. The data indicate that end-of-day dislocation mitigates the number of patents and the number of citations received by patents due to the associated short-termism of the firm's orientation, the long-term harm to a firm's equity values, and commensurate reduced incentives for employees to innovate. Our findings are robust to numerous robustness checks on subsamples of the data,

propensity score matching analyses, difference-in-differences tests for firms with and without dislocation, among other factors.

Unlike prior literature that shows a negative relation between patenting and liquidity, we observe a robust and significantly positive effect of liquidity on patenting. The positive effect of liquidity on innovation, however, is mitigated by the presence of end-of-day dislocation. The data also confirm the importance of country-level factors such as intellectual property rights across countries that encourage patenting.

Finally, unlike the negative effects of end-of-day manipulation on patents, we find an opposite positive effect of information leakage on patents for higher quality patents, and particularly in non-crisis periods. Insiders have, in some cases, pronounced incentives to engage in insider trading associated with announcement of innovations. Future research could examine specific cases in more detail, among other extensions related to those that we discussed in this paper.

References

Agrawal, A., Cooper, T., 2015. Insider trading before accounting scandals. Journal of Corporate Finance 34, 169–190

Aggarwal, R.K., Wu, G., 2006. Stock market manipulations. Journal of Business 79, 1915-1953.

Allen, F., Gale, D., 1992. Stock-price manipulation. Review of Financial Studies 5, 503-529.

Allen, F., Gorton, G., 1992. Stock price manipulation, market microstructure and asymmetric information. European Economic Review 36, 624-630.

Aharony, J., Liu, C., Yawson, A., 2015. Corporate litigation and executive turnover, Journal of Corporate Finance 34, 268-292.

Aitken, M., Cumming, D.J., and F. Zhan, 2015a. High frequency trading and end-of-day price dislocation, Journal of Banking and Finance, 59, 330-349.

Aitken, M., D.J. Cumming, D.J., and F. Zhan, 2015b. Exchange trading rules, surveillance, and suspected insider trading, Journal of Corporate Finance, 34, 311-330.

Allen, F., Gale, D., 1992. Stock-price manipulation. Review of Financial Studies 5, 503-529.

Allen, F., Gorton, G., 1992. Stock price manipulation, market microstructure and asymmetric information. European Economic Review 36, 624-630.

Allen, F., Litov, L., Mei, J., 2006. Large Investors, Price Manipulation, and Limits to Arbitrage: An Anatomy of Market Corners, Review of Finance 10(4), 645–693.

Atanasov, V., Davies, R. J., and Merrick Jr., J. J., 2015. Financial Intermediaries in the Midst of Market Manipulation: Did they protect the fool or help the Knave? Journal of Corporate Finance, 34, 210-234.

Ayyagari, M., Demirguc-Kunt, A., Maksimovic, V. 2014. Bribe payments and innovation in developing countries: Are innovating firms disproportionately affected? Journal of Financial and Quantitative Analysis 49(1), 51-75.

Ayyagari, M., Demirguc-Kunt, A., Maksimovic, V. 2011. Firm innovation in emerging markets: The role of finance, governance, and competition, Journal of Financial and Quantitative Analysis 56(6), 1545-1580.

Bebchuk, L.A., and C. Fershtman, 1994. Insider Trading and the Managerial Choice among Risky Projects, Journal of Financial and Quantitative Analysis 29, 1-14.

Bernile, G., Sulaeman, J., and Wang, Q., 2015. Institutional trading during a wave of corporate scandals: 'Perfect Payday'? Journal of Corporate Finance 34, 191-209.

Bereskin, F., Campbell II, T., Kedia, S., 2014. Philanthropy, corporate culture, and misconduct, Working Paper, University of Delaware.

Bereskin, F. L., Hsu, P.-H., & Rotenberg, W. 2018. The Real Effects of Real Earnings Management: Evidence from Innovation. Contemporary Accounting Research 35, 525-557.

Blind, K. 2012. The influence of regulations on innovation: A quantitative assessment for OECD countries, Research Policy 41, 391-400.

Bollen, N.P.B., and V. K. Pool, 2009. Do hedge fund managers misreport returns? Evidence from the pooled distribution, Journal of Finance, 64, 2257-2288.

Branstetter, L.G., Fisman, R., & Foley, C. F. 2006. Do stronger intellectual property rights increase international technology transfer? Empirical evidence from US firm-level panel data, Quarterly Journal of Economics, 121(1): 321-349

Brown, J. R., Fazzari, S. M., & Petersen, B. C. (2009). Financing Innovation and Growth: Cash Flow, External Equity, and the 1990s R&D Boom. Journal of Finance, 64(1), 151–185

Brown, J. R., Martinsson, G., and Petersen, B. C. (2013). Law, Stock Markets, and Innovation. Journal of Finance, 68(4), 1517–1549.

Chen, Y., Podolski, E.J., Rhee, S.G., and Veeraraghavan, M. 2014. Local gambling preferences and corporate innovative success, Journal of Financial and Quantitative Analysis 49(1), 77-106.

Comerton-Forde, C., Putniņš, T.J. 2014. Stock Price Manipulation: Prevalence and Determinants, Review of Finance 18(1), 23–66.

Cumming, D.J., B. Dannhauser, and S. Johan, 2015. Financial market misconduct and agency conflicts: A synthesis and future directions, Journal of Corporate Finance, 34, 150-168.

Cumming, D.J., S.A. Johan, and D. Li, 2011. Exchange Trading Rules and Stock Market Liquidity, Journal of Financial Economics 99(3), 651-671.

Ding, H. 2015. Innovation strategies and stock price informativeness. Retrieved from https://www.econstor.eu/handle/10419/110401

Du Plessis, M., Van Looy, B., Song, X & Magerman, T., 2009. "Data Production Methods for Harmonized Patent Indicators: Assignee sector allocation" EUROSTAT Working Paper and Studies, Luxembourg.

Fang, V.W., Tian, X., Tice, S., 2014. Does Stock Liquidity Enhance or Impede Firm Innovation? Journal of Finance 69, 2085-2125.

Ferreira, D., Manso, G., Silva, A., 2014. Incentives to innovate and the decision to go public or private. Review of Financial Studies 27, 256–300.

Fulghieri, P., Sevilir, M. 2009. Organizing and financing of innovation, and the choice between corporate and independent venture capital, Journal of Financial and Quantitative Analysis 44(6), 1291-1321.

Giannetti, M., Wang, T.Y., 2016. Corporate scandals and household stock market participation, Journal of Finance 71(6), 2591-2636.

Gerken, W., Dimmock, S., 2016. Regulatory oversight and return misreporting by hedge funds, Review of Finance 20, 795-821

Gerken, W., Dimmock, S., 2012. Predicting fraud by investment managers, Journal of Financial Economics 105, 153-173

Hall, B.H., Jaffe, A.B., Trajtenberg, M., 2001. The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools. National Bureau of Economic Research.

Hall, B.H., Jaffe, A.B., Trajtenberg, M., 2005. Market Value and Patent Citations. RAND Journal of Economics, 16-38.

Jackson, H.E., Roe, M.J., 2009. Public and private enforcement of securities laws: resource-based evidence. Journal of Financial Economics 93, 207-238.

Jarrow, R.A., 1994. Derivative security markets, market manipulation and option pricing theory. Journal of Financial and Quantitative Analysis 29, 241-261.

Jensen, M.C. 2005. Agency costs of overvalued equity. Financial Management 34, 5–19.

Karpoff, J., Koester, A., Lee, D.S., Martin, G.S., 2012. A critical analysis of databases used in financial misconduct research. Mays Business School Research Paper No. 2012-73.

Karpoff, J., Lee, D.S., Martin, G.S., 2008a. The consequences to managers for cooking the books. Journal of Financial Economics 88, 193-215.

Karpoff, J.M., Lee, D.S., Martin, G.S., 2008b. The consequences to managers for financial misrepresentation. Journal of Financial Economics 85, 66-101.

Karpoff, J.M., Lou, X., 2010. Short sellers and financial misconduct. Journal of Finance 65, 1879-1913.

Kyle, A. S., & Viswanathan, S. (2008). How to Define Illegal Price Manipulation. American Economic Review, 98(2), 274–279.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., 2006. What works in securities laws? Journal of Finance 61, 1-32.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1997. Legal determinants of external finance. Journal of Finance 52, 1131–1150.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1998. Law and finance. Journal of Political Economy 106, 1113–1155.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 2002. Investor protection and corporate valuation. Journal of Finance 57, 1147–1170.

Levine, R., C. Lin, and L. Wei, 2015. Insider trading and innovation, Working Paper, University of California, Berkeley.

Lyandres, E., and Palazzo, B. 2016. Cash holdings, competition, and innovation, Journal of Financial and Quantitative Analysis 51(6), 1823-1861.

Magerman T, Grouwels J., Song X. & Van Looy B., 2009. Data Production Methods for Harmonized Patent Indicators: Patentee Name Harmonization, EUROSTAT Working Paper.

Manso, G. (2011). Motivating Innovation. Journal of Finance, 66(5), 1823–1860.

Marciukaityte, D., Varma, R. (2008). Consequences of overvalued equity: Evidence from earnings manipulation, Journal of Corporate Finance 14(4), 418-430.

Mathers, A.M., Wang, B., Wang, X. (2017). Innovation and Price Informativeness. Financial Management 46(2), 523-546.

Merrick, J.J. Jr., Naik, N.Y., Yadav P.K., 2005. Strategic trading behavior and price distortion in a manipulated market: anatomy of a squeeze. Journal of Financial Economics 77, 171-218.

Meulbroek, L.K., 1992. An empirical analysis of illegal insider trading, Journal of Finance 47, 1661-1699.

Ni, S.X., Pearson, N.D., Poteshman, A.M., 2005. Stock price clustering on option expiration dates. Journal of Financial Economics 78, 49-87.

O'Connor, M., and Rafferty, M. 2012. Corporate governance and innovation, Journal of Financial and Quantitative Analysis 47(2), 397-413.

O'Hara, M., 2001. Overview: market structure issues in market liquidity, in Market Liquidity: Proceedings of a Workshop Held at the BIS, BIS Papers, No. 2, April, Basel, 1-8.

O'Hara, M., Mendiola, A.M., 2003. Taking stock in stock markets: the changing governance of exchanges. Unpublished working paper. Cornell University, NY.

Peng, L., and Röell, A., 2014. Managerial incentives and stock price manipulation, Journal of Finance 69(2), 587-526.

Peeters B., Song X., Callaert J., Grouwels J., Van Looy B., 2009. "Harmonizing harmonized patentee names: an exploratory assessment of top patentees" EUROSTAT working paper and Studies, Luxembourg.

Pirrong, S.C., 1993. Manipulation of the commodity futures market delivery process. Journal of Business 15, 335-370.

Pirrong, S.C., 1995a. The self-regulation of commodity exchanges: the case of market manipulation. Journal of Law and Economics 38, 141-206.

Pirrong, S.C., 1995b. Mixed manipulation strategies in commodity futures markets. Journal of Futures Markets 15, 13-38.

Röell, A., 1992. "Comparing the performance of stock exchange trading systems," In: J. Fingleton and D. Schoenmaker, (Eds.), The Internationalisation of Capital Markets and the Regulatory Response. Kluwer, Amsterdam.

Shen, C.H., Zhang, H., 2017. Tournament Incentives and Firm Innovation, Review of Finance, forthcoming.

Vismara, S., Paleari, S., Signori, A., 2015. Changes in underwriters' selection of comparable firms pre- and post-IPO: same bank, same company, different peers. Journal of Corporate Finance,

Wang, T., Winton, A., Yu, X. 2010. Corporate fraud and business conditions: Evidence from IPOs, Journal of Finance 65, 2255-2292.

Yung, C., 2016. Making waves: To innovate or be a fast second? Journal of Financial and Quantitative Analysis 51(2): 415-433.

Table 1
Connecting Market Microstructure to Innovation

This table summarizes prior literature and predictions on the relationship between market microstructure and innovation.

	Market Microstructure Events		
	End-of-Day (EOD) Dislocation	**Information Leakage**	**Predicted Impact on Innovation**
Panel A: First-Order Effects			
Improper valuation of current equity values	Positive	Positive	Over- or under-valuation of a firm's equity causes agency problems where management releases misinformation to justify valuations (Jensen, 2005; Marciukaityte and Varma, 2008), and in turn agency problems and short-termism impede innovation (Manso, 2011).
Effect on long-term equity value trends	Negative	Negative	Lower prices damage incentive to innovate when innovators are compensated with equity.
Ability to Raise Future Equity	Negative	Negative	Reduced ability to raise external equity has a negative impact on innovation (Brown et al., 2009, 2013)
Ability of Insiders to Profit on Proprietary Information		Positive	Ability of insiders to profit on proprietary information increases innovation as insiders that innovate gain exacerbated profits (Agarwal and Cooper, 2015 and Levine, 2015)
Long-term orientation of Firm's Management	Negative	Negative	Short-term orientation leads to less innovation activity (Manso, 2011)
Overall Predicted Impact on Innovation	**Hypothesis 1:** EOD Dislocation lowers innovation	**Hypothesis 2:** Insider trading raises innovation if the effect of insider profits outweighs all of the other effects.	

Panel B: Possible Second-Order Effects			
Stock price Informativeness	Negative	Positive	Incentive to innovate may be reduced because stock prices may reveal firms' private information on innovation progress to competitors through information leakage (Ding, 2015)
Liquidity	Negative	Negative	Liquidity lowers innovation if mergers are more likely (Fang et al., 2014), but raise innovation if ability to raise external capital increases (Brown et al., 2009, 2013)
Impact on Mergers	Negative	Negative	Mergers lower incentive to innovate as takeovers lead to employee layoffs. (Fang et al, 2014)

Table 2
Variable Definitions

Variable	Definition	Data source
INNOV_PAT(t+1)	Natural logarithm of one plus firm *i*'s total number of patents filed in year *t*+1.	PATSTAT
INNOV_CITE(t+1)	Natural logarithm of one plus firm *i*'s total number of citations received for patents filed in year *t*+1. The number of citations has been adjusted for truncation bias using the citation lag distribution.	PATSTAT
INNOV_PAT_GRNT(t+1)	Natural logarithm of one plus firm *i*'s total number of patents filed and eventually granted in the year t+1	PATSTAT
INNOV_PAT_GRNT_ADJ(t+1)	Natural logarithm of one plus firm *i*'s total number of patents filed and eventually granted in the year t+1, which has been adjusted for truncation bias using the grant lag distribution.	PATSTAT
Average_industry-year_patents(t-1)	The average INNOV_PAT(t-1) for an industry within each country, in the year t.	PATSTAT
CHANGE_NUM_PAT	Change in the number of patents computed as firm *i's* total number of patents filed in the year t+1 minus firm *i's* total number of patents filed in the year t-1	PATSTAT
CHANGE_LN_PAT	Natural logarithm one plus firm *i's* total number of patents filed in the year t+1 minus the natural logarithm of one plus firm *i's* total number of patents filed in the year t-1.	PATSTAT
EOD_Dummy	Indicates if a firm i has experienced end-of-day (EOD) dislocation in year t CMCRC and SMARTS surveillance staff constructed the dislocation of EOD price case by looking at the price change between the last trade price (P_t) and the last available trade price 15 minutes before the continuous trading period ends (P_{t-15}). For securities exchanges that have a closing auction, the close price at auction is used ($P_{auction}$). A price movement is dislocated if it is four standard deviations away from the mean price change during the benchmarking period for the past 100 trading	CMCRC

	days. To be considered as a dislocation of EOD price case, at least 50% of the price dislocation has to revert at open on the next trading day. Hence, the price movement between the last trade price (P_t) and the next day opening price (P_{t+1}), and between the last trade price (P_t) and the last available trade price 15 minutes before the continuous trading period ends (P_{t-15}) has to be more than 50%. ($P_{auction\ or}$ P_t - P_{t+1})/($P_{auction\ or}P_t$ - P_{t-15}) ≥50%. Source: Capital Markets Cooperative Research Centre (CMCRC) and SMARTS, Inc.	
EOD_Dummy_First(t)	Indicates if firm i has experienced end-of-day (EOD) dislocation in year t, under the condition that firm i never previously experienced EOD dislocation until year t.	CMCRC
EOD_Dummy_Subsequent(t)	Indicates if firm i has experienced any EOD price dislocation in year t, under the condition that it was manipulated before year t.	CMCRC
Num_EOD_Cases_First(t)	Number of times a firm has had EOD price dislocation in year t, under the condition that firm i has never previously experienced EOD price dislocation until year t.	CMCRC
Num_EOD_Cases_Subsequent(t)	Number of times in year t a firm has experienced EOD price dislocation, under the condition that it experienced EOD price dislocation before year t.	CMCRC
EOD_Dummy_Positive(t)	Indicates if firm i has experienced more positive EOD price dislocations than negative price dislocations in year t.	CMCRC
Infoleak_Dummy(t)	Indicates if firm i has experienced information leakage in year t. CMCRC and SMARTS surveillance staff constructed this variable. CMCRC and SMARTS first examined all news releases from the exchanges themselves. CMCRC and SMARTS measured the return to the security in the six days prior to the announcement up to the two days after the announcement. They double-checked the Thompson Reuters News Network to ensure that they did not miss any important news announcements. They consider only news events that have no companion news announcements that could explain price movements in the six days before and the two days after the relevant announcement that could explain the price movement. For each news announcement, a price movement is abnormal if it is three standard	CMCRC

	deviations away from the mean abnormal return during the 250-day benchmarking period ending 10 days before the news release. To be included in our sample, the stock must have at least 150 days' worth of trading activities. A one-factor market model based on the market index for each exchange is used to calculate daily abnormal returns. To be included in the final data set as a suspected information leakage case, the CAR around each event over the period [t-6, t+2] must be three standard deviations away from the normal nine-day CAR for each individual stock. Once the suspected information leakage case is defined, abnormal profit per case is calculated as the trading-volume-multiple abnormal returns from six days before to the day before the news announcement. SMARTS surveillance staff independently examines the data to distinguish between market anticipation and suspected insider trading; since SMARTS includes as insider trading only large movements that are three-standard-deviation changes, the possibility that insider trades could be viewed as market anticipation is mitigated.	
Num_Infoleak_Cases(t)	Number of times a firm has experienced information leakage in year t.	CMCRC
Strong(Weak)_EOD_First(t)	Indicates if firm i has experienced any EOD price dislocation in year t during the days more likely to experience manipulation (except on days more likely to experience manipulation), under the condition that firm i never previously experienced EOD dislocation until year t. Manipulation is considered more common during the last three trading days of a month.	CMCRC
Strong(Weak)_EOD_Subsequent(t)	Indicates if firm i has experienced any EOD price dislocation in year t during the days more likely to experience manipulation (except on days more likely to experience manipulation), under the condition that it was manipulated before year t. Manipulation is considered more common during the last three trading days of a month.	CMCRC
Strong(Weak)_Infoleak_First(t)	Indicates if firm i has experienced any information leakage in year t during the days more likely to experience manipulation (except on days more likely to experience manipulation), under the condition firm i never previously experienced information leakage until year t. Manipulation is considered more common during the last three	CMCRC

	trading days of a month.	
Strong(Weak)_Infoleak_Subsequent(t)	Indicates if firm i has experienced any information leakage in year t during the days more likely to experience manipulation (except on days more likely to experience manipulation), under the condition that it was manipulated before year t. Manipulation is considered more common during the last three trading days of a month.	CMCRC
Liquidity(t)	Denotes the natural logarithm of the inverse of the AMIHUD illiquidity variable. The AMIHUD illiquidity variable is computed as: $$A_{ij} = \frac{1}{D_{iy}} \sum_{i=1}^{D_{iy}} \frac{\lvert r_{it} \rvert}{Dvol_{it}},$$ where A_{iy} is the AMIHUD measure of firm i in year y. R_{it} and $Dvol_{it}$ are daily return and daily dollar trading volume for stock i on day t. D_{iy} is the number of days with an available ratio in year y. A higher AMIHUD value indicates a higher level of illiquidity. Hence, the logarithm of the inverse of AMIHUD would be a measure of liquidity rather than illiquidity.	Datastream
MV_Decile(t)	Market value decile variable takes the value of 1 to 10, based on the market value decile to which firm i belongs, within each country-year grouping, at the end-of-year t.	Datastream
ROA(t)	Return on assets, defined as the Income before extraordinary items, divided by book value of total assets, measured at the end of fiscal year t.	Datastream
RDTA(t)	Research and development expenditures divided by book value of total assets measured at the end of fiscal year t, set to zero if missing.	Datastream
PPETA(t)	Property, plant, and equipment divided by book value of total assets measured at the end of fiscal year t.	Datastream
LEV(t)	Firm i's leverage ratio, defined as book value of debt, divided by book value of total assets, measured at the end of fiscal year t.	Datastream
CAPEXTA(t)	Capital expenditures scaled by book value of total assets, measured at the end of fiscal year t.	Datastream

Q(t)	Firm i's market-to-book ratio during fiscal year t, calculated as the market value of equity, plus book value of debt, divided by book value of assets.	Datastream
LN_Firm_Age(t)	Natural logarithm of one plus firm *i*'s age, approximated by the number of years listed on Datastream.	Datastream
IPR_Index(t)	Intellectual Property Rights Index obtained from the International Property Rights Index Report published from 2007 to 2010. For 2003 to 2006, we use the oldest available index value from 2007.	Property Right Alliance
Enforcement_index	The index is formed by adding the rule of law, the efficiency of the judiciary, risk of expropriation, repudiation of contracts by government, and corruption variables provided by LLSV and the scaling index to be between 0 and 1 (1998)	LLSV
Interaction_Liquidity_EOD(t)	Interaction variable computed as EOD_Dummy_Subsequent(t) x Liquidity(t)	Datastream and CMRC
Interaction_Enforcement_EOD(t)	Interaction variable computed as EOD_Dummy_Subsequent(t) x Enforcement_index(t)	LLSV and CMCRC
Interaction_IPR_EOD(t)	Interaction variable computed as EOD_Dummy_Subsequent(t) x IPR_index(t)	Property rights alliance and CMCRC

Table 3
Summary Statistics

Table 3 reports the summary statistics for variables constructed using a sample of public firms from Australia, Canada, China, India, Japan, New Zealand, Singapore, Sweden, and the United States. The Innovation variables are measured from 2004 to 2011. The EOD / Infoleak variables and the control variables are measured from 2003 to 2010.

Description	N	Mean	25th percentile	Median	75th percentile	95th percentile	SD	Max	Min
INNOV_PAT(t+1)	131129	0.3266	0.0000	0.0000	0.0000	2.5649	0.9580	5.2523	0.0000
INNOV_PAT_GRNT(t+1)	131129	0.2355	0.0000	0.0000	0.0000	1.9459	0.7747	4.4886	0.0000
INNOV_PAT_GRNT_ADJ(t+1)	131129	0.2609	0.0000	0.0000	0.0000	2.1803	0.8396	4.7474	0.0000
INNOV_CITE(t+1)	131129	0.3745	0.0000	0.0000	0.0000	3.8687	1.3410	7.2374	0.0000
EOD_Dummy_First(t)	131129	0.0765	0.0000	0.0000	0.0000	1.0000	0.2657	1.0000	0.0000
EOD_Dummy_Subsequent(t)	131129	0.1206	0.0000	0.0000	0.0000	1.0000	0.3257	1.0000	0.0000
Num_EOD_Cases_First(t)	131129	0.7077	0.0000	0.0000	0.0000	6.0000	2.7109	16.0000	0.0000
Num_EOD_Cases_Subsequent(t)	131129	1.2821	0.0000	0.0000	0.0000	11.0000	3.9860	22.0000	0.0000
Infoleak_Dummy(t)	131129	0.0789	0.0000	0.0000	0.0000	1.0000	0.2696	1.0000	0.0000
Num_Infoleak_Cases(t)	131129	0.0902	0.0000	0.0000	0.0000	1.0000	0.3236	2.0000	0.0000
Liquidity(t)	126513	2.5603	-1.3837	2.9381	6.3070	9.6037	4.6318	11.8470	-6.6823
ROA(t)	103963	-0.0683	-0.0287	0.0196	0.0594	0.1571	0.3871	0.3242	-2.7669
RDTA(t)	104159	0.0217	0.0000	0.0000	0.0062	0.1275	0.0677	0.4726	0.0000
PPETA(t)	103377	0.2910	0.0608	0.2263	0.4566	0.8260	0.2606	0.9495	0.0000
LEV(t)	104030	0.2154	0.0103	0.1576	0.3439	0.6409	0.2274	1.1153	0.0000
CAPEXTA(t)	103210	0.0583	0.0078	0.0274	0.0681	0.2369	0.0865	0.4957	0.0000
Q(t)	99383	1.7107	0.6198	0.9766	1.6834	4.9931	2.7493	21.6262	0.0893
LN_Firm_Age(t)	131121	2.8475	2.4849	2.9444	3.2581	3.7612	0.5483	3.7612	1.0986
IPR_Index(t)	131129	7.1834	7.5000	8.0000	8.2000	8.6000	1.5445	8.6000	3.5000
Enforcement_index	123971	0.8579	0.9189	0.9196	0.9276	0.9276	0.1311	0.9616	0.5965
Interaction_Liquidity_EOD(t)	126511	0.1640	0.0000	0.0000	0.0000	2.1306	1.2924	9.2867	-9.2427
Interaction_Enforcement_EOD(t)	123971	-0.0097	0.0000	0.0000	0.0000	0.0697	0.0633	0.1037	-0.2613
Interaction_IPR_EOD(t)	131129	-0.0604	0.0000	0.0000	0.0000	0.8166	0.6179	1.4166	-3.6834

Table 4
Comparison of the Percentage of Change in the Number of Patent Applications

Table 3 (IV?) compares the percentage of change in the number of patents between t-1 and t+1, for both firms that have experienced end-of-day price manipulation (information leakage) and those that have not experienced end-of day-price manipulation (information leakage). The sample has been split into High IPR and Low IPR, where High IPR are observations with an IPR index value over 5 and Low IPR are observations with an IPR index value less than 5. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

	End-of-Day Manipulation						**Information Leakage**					
	% change in the number of patent applications						**% change in the number of patent applications**					
	N	**Low IPR firms**	**N**	**High IPR firms**	**N**	**All firms**	**N**	**Low IPR firms**	**N**	**High IPR firms**	**N**	**All firms**
Panel A: Number of Patent Applications												
Firms that have been manipulated [A]	6,020	-0.2438	19,826	0.1131	25,846	0.0300	946	8.6446	9,404	4.2493	10,350	4.6510
Firms that have not been manipulated [B]	15,711	4.5722	89,572	0.9030	105,283	1.4506	20,785	2.9920	99,994	0.4317	120,779	0.8723
Difference [A] - [B]		**-4.8160** ***		**-0.7899**		**-1.4206** **		**5.6527** ***		**3.8176** ***		**3.7787** ***
Panel B: Number of Patent Citations												
Firms that have been manipulated [A]	6,020	0.5653	19,826	7.2946	25,846	5.7272	946	2.6729	9,404	21.8940	10,350	20.1372
Firms that have not been manipulated [B]	15,711	4.4594	89,572	7.5816	105,283	7.5116	20785	3.4129	99,994	6.1787	120,779	5.7027
Difference [A] - [B]		**-3.8941** **		**-0.2870**		**-1.7844**		**-0.7400**		**15.7153** ***		**14.4344** ***

Table 5
Pooled OLS Specification

Table 5, Panel A [B] reports Pooled OLS regression results of the model INNOV_PAT(i,t+1) [INNOV_CITE(i,t+1)] = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c'Controls + YR(t) + Firm(i) + error(i,t). INNOV_PAT(i,t+1) is the natural logarithm of one plus firm i's total number of patents filed in year t+1. INNOV_CITE(i,t+1) is the natural logarithm of one plus firm i's total number of citations received for patents filed in year t+1, which has been adjusted for truncation bias using the citation lag distribution. EOD_Dummy_First [EOD_Dummy_Subsequent] indicates if firm i has experienced end-of-day (EOD) dislocation in year t, under the condition that firm i never previously experienced [has previously experienced] EOD dislocation. Infoleak_Dummy indicates if firm i has experienced information leakage in year t. Similarly, Num_EOD_Cases_First, Num_EOD_Cases_Subsequent and Num_Infoleak_cases measure the number of times firm i has experienced EOD or Information leakage in year t. EOD_Dummy_Positive(t) indicates if firm i has experienced more positive EOD price dislocations than negative price dislocations in year t. Liquidity(t) is the natural logarithm of the inverse of the AMIHUD illiquidity variable. Interaction_Liquidity_EOD(t) mixes Liquidity(t) and EOD_Dummy_Subsequent variables. Intellectual Property Rights Index, IPR_Index(t), is the Intellectual Property Rights Index obtained from the International Property Rights Index Report. Market value decile is (MV_Decile(t)), to which firm i belongs within each country-year; Return on Assets is (ROA(t)); Property plant and equity to total assets is (PPTA(t)); leverage measured as the book value of debt to book value of assets is (LEV(t)); Capital expenditure to total assets is (CAPEXTA(t)); Tobin's Q is (Q(t)); and natural logarithm of one plus firm i's age, approximated by the number of years listed on Datastream is (LN_Firm_Age(t)), used as controls in all the models. No time invariant variables or interactions of time invariant variables are included in this model. Year fixed effects YR(i) and firm fixed effects Firm(i) are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

Panel A: Innovation measured by INNOV_PAT(i, t+1)

	(1)		(2)		(3)		(4)	
EOD_Dummy(t)	-0.00803	**						
EOD_Dummy_First(t)			0.00380		-		0.00365	
EOD_Dummy_Subsequent(t)			-0.01742	***	-		-0.01328	***
EOD_Dummy_Positive(t)			-0.00120		-0.00368		-0.00145	
Infoleak_dummy(t)	-0.00640		-0.00622		-		-0.00624	
Num_EOD_Cases_First(t)			-		0.00061		-	
Num_EOD_Cases_Subsequent(t)			-		-0.00122	***	-	
Num_Infoleak_cases(t)			-		-0.00372		-	
Liquidity(t)	0.01235	***	0.08598	***	0.08624	***	0.01266	***
Interaction_Liquidity_EOD (t)			-		-		-0.00267	**
IPR_index(t)	0.08491	***	0.01228	***	0.01218	***	0.08594	***
MV_Decile(t)	0.00246	*	0.00258	*	0.00259	*	0.00256	*
ROA(t)	-0.00468		-0.00483		-0.00482		-0.00498	
PPETA(t)	0.00530		0.00547		0.00535		0.00537	
LEV(t)	0.02556	**	0.02618	**	0.02599	**	0.02637	**
CAPEXTA(t)	-0.03452	**	-0.03519	**	-0.03475	**	-0.03553	**
Q(t)	-0.00132	*	-0.00135	*	-0.00134	*	-0.00136	*
Year and Firm fixed effects	Included		Included		Included		Included	
Sector fixed effects	Included		Included		Included		Included	
Number of observations used	97148		97,148		97,148		97148	

Adjusted R2	0.9106		0.9106		0.9106		0.9106	
Panel B: Innovation measured by INNOV_CITE(i, t+1)								
	(1)		**(2)**		**(3)**		**(4)**	
EOD_Dummy(t)	-0.03222	***						
EOD_Dummy_First(t)			0.00070		-		-0.00030	
EOD_Dummy_Subsequent(t)			-0.08753	***	-		-0.05907	***
EOD_Dummy_Positive(t)			0.03086	**	0.01836		0.02916	**
Infoleak_dummy(t)	0.01661		0.01725		-		0.01707	
Num_EOD_Cases_First(t)			-		0.00043		-	
Num_EOD_Cases_Subsequent(t)			-		-0.00554	***	-	
Num_Infoleak_cases(t)			-		0.01494		-	
Liquidity(t)	0.02333	***	0.02309	***	0.21432	***	-0.01838	***
Interaction_Liquidity_EOD (t)			-		-		0.21350	***
IPR_index(t)	0.20886	***	0.21377	***	0.02264	***	0.02569	***
MV_Decile(t)	0.01911	***	0.01962	***	0.01961	***	0.01951	***
ROA(t)	-0.02831	***	-0.02887	***	-0.02875	***	-0.02994	***
PPETA(t)	0.02721		0.02823		0.02768		0.02751	
LEV(t)	0.03178		0.03438		0.03303		0.03562	
CAPEXTA(t)	-0.18480	***	-0.18833	***	-0.18587	***	-0.19065	***
Q(t)	-0.00414	***	-0.00422	***	-0.00417	***	-0.00428	***
Year and Firm fixed effects	Included		Included		Included		Included	
Sector fixed effects	Included		Included		Included		Included	
Number of observations used	97148		97,148		97,148		97148	
Adjusted R2	0.7259		0.72600		0.72600		0.7262	

Table 6
Random Effects Specification

Table 6, Panel A [B] reports Firm Random Effects regression results of the model INNOV_PAT(i,t+1) [INNOV_CITE(i,t+1)] = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c1'Country_variable(Enforcement and IPR) + c2'Interaction_Country_variable_EOD + c3*Interaction_Liquidity_EOD + d'Controls + YR(t) + Sector(i) + error(i,t). INNOV_PAT(i,t+1) is the natural logarithm of one plus firm i's total number of patents filed in year t+1. INNOV_CITE(i,t+1) is the natural logarithm of one plus firm i's total number of citations received for patents filed in year t+1, which has been adjusted for truncation bias using the citation lag distribution. EOD_Dummy_First [EOD_Dummy_Subsequent] indicates if firm i has experienced end-of-day (EOD) dislocation in year t, under the condition that firm i never previously experienced [has previously experienced] EOD dislocation. Infoleak_Dummy indicates if firm i has experienced information leakage in year t. Similarly, Num_EOD_Cases_First, Num_EOD_Cases_Subsequent and Num_Infoleak_cases measure the number of times firm i has experienced EOD or Information leakage in year t. EOD_Dummy_Positive(t) indicates if firm i has experienced more positive EOD price dislocations than negative price dislocations in year t. Liquidity(t) is the natural logarithm of the inverse of the AMIHUD illiquidity variable. The Enforcement_index is formed by adding the rule of law, efficiency of judiciary, risk of expropriation, repudiation of contracts by government, and corruption variables provided by LLSV, and scaling the index to be between 0 and 1 (1998). The Intellectual Property Rights index, IPR_Index, is obtained from the International Property Rights Index report. Interaction_Liquidity_EOD, Interaction_Enforcement_EOD, and Interaction_IPR_EOD mixes the Liquidity(t), Enforcement_index(t) and IPR_Index(t), respectively, with the EOD_Dummy_Subsequent variable. Market value decile is (MV_Decile(t)), to which firm i belongs within each country-year; Return on Assets is (ROA(t)); Property plant and equity to total assets is (PPTA(t)); leverage measured as the book value of debt to book value of assets is (LEV(t)); Capital expenditure to total assets is (CAPEXTA(t)); Tobin's Q is (Q(t)); and the natural logarithm of one plus firm i's age, approximated by the number of years listed on Datastream is (LN_Firm_Age(t)), used as controls in all the models. Year fixed effects and industry fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

Panel A: Innovation Measured by INNOV_PAT(i,t+1)

	(1) Simple EOD Dummy		(2) EOD Dummy		(3) Number of EOD Cases		(4) Enforcement index		(5) IPR Index		(6) EOD & Liquidity	
EOD_Dummy(t)	-0.01345	***										
EOD_Dummy_First(t)			-0.00108				0.00080		-0.00048		0.00362	
EOD_Dummy_Subsequent(t)			-0.02415	***			-0.01158	**	-0.02519	***	-0.02119	***
Infoleak_dummy(t)	-0.00333		-0.00313				-0.00454		-0.00491		-0.00493	
Num_EOD_Cases_First(t)					0.00017							
Num_EOD_Cases_Subsequent(t)					-0.00159	***						
Num_Infoleak_cases(t)					-0.00212							
Liquidity(t)	0.03245	***	0.03244	***	0.03230	***	0.02548	***	0.03014	***	0.03048	***

Enforecement_index							1.39727	***				
IPR_Index									0.10116	***	0.10152	***
Interaction_Enforcement_EOD							0.03676	*				
Interaction_IPR_EOD									0.00159			
Interaction_Liquidity_EOD											-0.00266	**
MV_Decile(t)	0.00236	*	0.00246	*	0.00242	*	0.00579	***	0.00461	***		***
ROA(t)	-0.01919	***	-0.01930	***	-0.01929	***	-0.01656	***	-0.01923	***	0.00458	***
PPETA(t)	-0.00199		-0.00182		-0.00191		0.01521	*	0.00904		-0.01938	
LEV(t)	0.01463		0.01526		0.01498		0.02433	**	0.03146	***	0.00890	***
CAPEXTA(t)	-0.07966	***	-0.08043	***	-0.07995	***	-0.05881	***	-0.07135	***	0.03156	***
Q(t)	-0.00298	***	-0.00300	***	-0.00297	***	-0.00395	***	-0.00389	***	-0.07175	***
LN_Firm_Age(t)	0.28193	***	0.28267	***	0.28291	***	0.27571	***	0.26254	***	-0.00390	***
Year fixed effects	Included		Included		Included		Included		Included		Included	
Industry fixed effects	Included		Included		Included		Included		Included		Included	
Number of observations used	97,148		97,148		97,148		90,272		97,148		97,148	
R2	0.2310		0.2314		0.2310		0.2550		0.2543		0.2541	

Panel B: Innovation Measured by INNOV_CITE(i,t+1)

	(1) Simple EOD Dummy		(2) EOD Dummy		(3) Number of EOD Cases		(4) Enforcement index		(5) IPR Index		(6) EOD & Liquidity	
EOD_Dummy_First(t)	-0.04841	***	0.00668				0.01014		0.01059		0.00861	
EOD_Dummy_Subsequent(t)			-0.09415	***			-0.07728	***	-0.08366	***	-0.05779	***
Infoleak_dummy(t)	0.02378	**	0.02463	**			0.02532	**	0.01797		0.01771	
Num_EOD_Cases_First(t)					0.00065							
Num_EOD_Cases_Subsequent(t)					-0.00604	***						
Num_Infoleak_cases(t)					0.01909	**						
Liquidity(t)	0.06373	***	0.06359	***	0.06333	***	0.05979	***	0.06218	***	0.06357	***
Enforecement_index							1.44248	***				
IPR_Index		***							0.16000	***	0.15408	***
Interaction_Enforcement_EOD							-0.22679	***				
Interaction_IPR_EOD									-0.03288	***		

Interaction_Liquidity_EOD											-0.01676	***
MV_Decile(t)	0.01612	***	0.01654	***	0.01632	***	0.02055	***	0.01768	***	0.01881	***
ROA(t)	-0.07764		-0.07782	***	-0.07787	***	-0.06956	***	-0.06673	***	-0.06829	***
PPETA(t)	-0.00089	*	-0.00010		-0.00025		0.03112		0.03267	*	0.03136	
LEV(t)	-0.04747	***	-0.04453	*	-0.04585	*	0.00319		0.00656		0.00769	
CAPEXTA(t)	-0.25134	***	-0.25371	***	-0.25237	***	-0.20404	***	-0.22188	***	-0.21957	***
Q(t)	-0.00745	***	-0.00753	***	-0.00746	***	-0.00915	***	-0.00811	***	-0.00817	***
LN_Firm_Age(t)	0.26087	***	0.26412	***	0.26421	***	0.23686	***	0.22725	***	0.22608	***
Year fixed effects	Included		Included		Included		Included		Included		Included	
Industry fixed effects	Included		Included		Included		Included		Included		Included	
Number of observations used	97148		97,148		97,148		90,272		97,148		97,148	
R2	0.2005		0.2309		0.2305		0.2750		0.2687		0.2534	

Table 7
Robustness Checks

Table 7 reports various robustness check regression results of the Firm Random Effects model INNOV_PAT(i,t+1) = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c1'IPR_Index + d1*Liquidity + d2*Interaction_Liquidity_EOD + e'Controls + YR(t) + Industry(i) + error(i,t). Year fixed effects YR(i) and Industry(i) fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

Panel A: Model 1 excludes US observations from the sample. Model 2 excludes the financial crisis years of 2007 and 2008. Model 3 includes only the financial crisis year observations. Model 4 uses variables without any winsorization.

Panel B: Model 1 and 2 uses patent applications that are eventually granted, which has been adjusted for truncation bias as the dependent variable. Model 3 uses patent applications that are eventually granted as the dependent variable. Model 4 uses Citations per patent computed as the Log(1 + (Number of citations received in the year t+1 / Number of patent application in the year t)).

Panel C: Model 1 clusters the standard errors by industry-year. Model 2 clusters the standard errors by country-year. Model 3 winsorizes the variables at 2.5% and 97.5%. Model (4) winsorizes the variables at 5% and 95%.

Panel A: Robustness to Non-US Observations, Exclusion of Crisis Years, Only Crisis Years, Other Measures of Innovation, and No Winsorization

	(1) Non-US		(2) Excludes Crisis Years		(3) Only Crisis Years		(4) Without Winsorization	
EOD_Dummy_First(t)	0.00048		-0.00253		-0.02384	***	0.00048	
EOD_Dummy_Subsequent(t)	-0.02105	***	-0.02430	***	-0.05051	***	-0.01978	***
Infoleak_dummy(t)	-0.00339		-0.00286		-0.01769	**	-0.00498	
IPR_Index(t)	0.11904	***	0.10969	***	0.09817	***	0.10256	***
Liquidity(t)	0.03236	***	0.03587	***	0.05556	***	0.02982	***
Interaction_Liquidity_EOD(t)	-0.00336	**	-0.00224		-0.00535	**	-0.00200	
MV_Decile(t)	0.00060		0.00451	***	0.01706	***	0.00281	**
ROA(t)	-0.01983	***	-0.02518	***	-0.04814	***	-0.00001	
PPETA(t)	0.00927		0.00549		0.02132		0.00764	
LEV(t)	0.03307	***	0.03960	***	-0.04294	**	0.00006	
CAPEXTA(t)	-0.07043	***	-0.09071	***	-0.02307		-0.00060	

Q(t)	-0.00354	***	-0.00520	***	-0.00610	***	0.00000	***
LN_Firm_Age(t)	0.37413	***	0.25431	***	0.24447	***	0.28811	***
Year fixed effects	Included		Included		Included		Included	
Industry fixed effects	Included		Included		Included		Included	
Number of observations used	66,195		70,752		26,396		97148	
R2	0.2935		0.2610		0.2788		0.2474	

Panel B: Robustness to Applied and Granted Measure of Innovation

	(1) Adjusted Applied & Granted Patents		(2) Adjusted Applied & Granted Patents		(3) Applied & Granted Patents		(4) Citations per Patent	
EOD_Dummy(t)	-0.00949	***						
EOD_Dummy_First(t)			-0.00449		-0.00086		0.01029	
EOD_Dummy_Subsequent(t)			-0.01460	***	-0.01001	***	-0.02659	***
Infoleak_dummy(t)	0.01346	***	0.01355	***	0.01532	***	0.00607	
IPR_Index(t)	0.10698	***	0.10697	***	0.10144	***	0.06107	***
Liquidity(t)	0.03141	***	0.03133	***	0.02817	***	0.02939	***
Interaction_Liquidity_EOD(t)	-0.00020		0.00039		0.00037		-0.00886	***
MV_Decile(t)	0.00334	***	0.00338	***	0.00514	***	0.00615	***
ROA(t)	-0.01989	***	-0.01988	***	-0.02090	***	-0.03169	***
PPETA(t)	0.00433		0.00444		0.00829		0.00124	
LEV(t)	0.01182		0.01206		0.01698	*	-0.00602	
CAPEXTA(t)	-0.08512	***	-0.08535	***	-0.09796	***	-0.09081	***
Q(t)	-0.00424	***	-0.00424	***	-0.00439	***	-0.00320	***
LN_Firm_Age(t)	0.19679	***	0.19715	***	0.17644	***	0.06157	***
Year fixed effects	Included		Included		Included		Included	
Industry fixed effects	Included		Included		Included		Included	
Number of observations used	97,148		97,148		97,148		97,148	
R2	0.2377		0.2378		0.2357		0.1656	

Panel C : Robustness to Various Types of Clustering of Standard Errors and Different Levels of Winsorization

	(1) Cluster by Industry-Year		(2) Cluster by Country-Year		(3) Winsor at 2.5% and 97.5%		(4) Winsor at 5% and 95%	
EOD_Dummy_First(t)	-0.00071		-0.00071		-0.00139		-0.00134	
EOD_Dummy_Subsequent(t)	-0.02119	***	-0.02119	**	-0.02174	***	-0.01995	***
Infoleak_dummy(t)	-0.00493		-0.00493		-0.00484		-0.00423	
IPR_Index(t)	0.10152	***	0.10152	***	0.09500	***	0.07961	***
Liquidity(t)	0.03048	***	0.03048	***	0.03010	***	0.02810	***
Interaction_Liquidity_EOD(t)	-0.00266		-0.00266		-0.00234	**	-0.00158	
MV_Decile(t)	0.00458	***	0.00458		0.00422	***	0.00296	***
ROA(t)	-0.01938	***	-0.01938	***	-0.02761	***	-0.04117	***
PPETA(t)	0.00890		0.00890		0.00439		-0.00010	
LEV(t)	0.03156	***	0.03156	*	0.03268	***	0.01929	*
CAPEXTA(t)	-0.07175	***	-0.07175	***	-0.07849	***	-0.07916	***
Q(t)	-0.00390	***	-0.00390	***	-0.00692	***	-0.00766	***
LN_Firm_Age(t)	0.26229	***	0.26229	***	0.22041	***	0.16339	***
Year fixed effects	Included		Included		Included		Included	
Industry fixed effects	Included		Included		Included		Included	
Number of observations used	97,148		97,148		97,148		97,148	
R2	0.2541		0.2541		0.2596		0.2611	

Table 8
Liquidity Deciles

Table 8 reports the Firm Random Effects regression results of the model INNOV_PAT(i,t+1) = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c1'IPR_Index +d1*Liquidity + e'Controls + YR(t) + Industry(i) + error(i,t), for the 10th, 20th, 80th, and 90th deciles of the Liquidity(t) measure. Year fixed effects YR(i) and Industry(i) fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

	(1) Top 10th Decile of Liquidity		(2) Top 20th Decile of Liquidity		(3) Bottom 80th Decile of Liquidity		(4) Bottom 90th Decile of Liquidity	
EOD_Dummy_First(t)	-0.00004		-0.00776		-0.01061		0.02004	
EOD_Dummy_Subsequent(t)	-0.05043	***	-0.03836	***	0.00001		-0.00236	
Infoleak_dummy(t)	-0.00795		-0.00640		-0.01753	***	-0.02460	***
IPR_Index	0.14863	***	0.13150	***	0.01050	**	0.00508	
Liquidity(t)	0.10636	***	0.08290	***	0.00314	*	-0.00103	
MV_Decile(t)	0.03925	***	0.02642	***	-0.00109		-0.00121	
ROA(t)	0.06544		0.02360		-0.00150		-0.00339	
PPETA(t)	0.13913		0.12528	**	-0.00572		0.00283	
LEV(t)	0.08000		0.00050		-0.00559		-0.00268	
CAPEXTA(t)	-0.11891		-0.05173		-0.01386		-0.01844	
Q(t)	-0.02638	**	-0.02499	***	-0.00001		-0.00024	
LN_Firm_Age(t)	0.43894	***	0.36686	***	0.00454		0.00900	
Year fixed effects	Included		Included		Included		Included	
Industry fixed effects	Included		Included		Included		Included	
Number of observations used	11,817		23,572		13,244		6,042	
R2	0.3685		0.3331		0.0155		0.0236	

Table 9
Manipulation on Month End Dates

Table 9 reports the regression results of the Firm Random Effects model INNOV_PAT(i,t+1) = a + b1'Strong(Weak)_EOD_Dummy_First(i, t) + b2'Strong(Weak)_EOD_Dummy_Subsequent(i,t) + c1'Strong(Weak)_Infoleak_Dummy_First(i,t) + c2'Strong(Weak)_Infoleak_Dummy_Subsequent + c1'IPR_Index +d1*Liquidity + e'Controls + YR(t) + Industry(i) + error(i,t). The Strong form of EOD and Infoleak considers only EOD / Infoleak cases occurring during the last three trading days of the month. Model 1 includes all the firms in the sample and uses only strong form manipulation dummies. Model 2 excludes all firms that were weakly manipulated from the sample and uses only strong form manipulation dummies. Model 3 includes all the firms in the sample and uses both strong form and weak form manipulation dummies. Year fixed effects and industry fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

	(1) Including Weakly Manipulated Firms		(2) Excluding Weakly Manipulated Firms		(3) Including Weak Manipulation Dummies	
Strong_EOD_Dummy_First(t)	-0.00546		-0.01260	*	0.00052	
Strong_EOD_Dummy_Subsequent(t)	-0.01887	**	-0.03999	***	-0.02862	***
Strong_Infoleak_Dummy_First(t)	0.00540		0.00919		0.01114	
Strong_Infoleak_Dummy_Subsequent(t)	-0.05905	**	-0.05696	*	-0.06027	**
Weak_EOD_Dummy_First(t)					-0.00202	
Weak_EOD_Dummy_Subsequent(t)					-0.02509	***
Weak_Infoleak_Dummy_First(t)					0.00275	
Weak_Infoleak_Dummy_Subsequent(t)					-0.01890	***
IPR_Index(t)	0.10136	***	0.10881	***	0.10147	***
Liquidity(t)	0.03000	***	0.03323	***	0.03014	***
MV_Decile(t)	0.00432	***	0.00511	***	0.00457	***
ROA(t)	-0.01909	***	-0.02005	***	-0.01928	***
PPETA(t)	0.00890		0.00768		0.00919	
LEV(t)	0.03033	***	0.03066	***	0.03131	***
CAPEXTA(t)	-0.07083	***	-0.08019	***	-0.07156	***
Q(t)	-0.00383	***	-0.00373	***	-0.00390	***
LN_Firm_Age(t)	0.26263	***	0.26184	***	0.26315	***
Year and industry fixed effects	Included		Included		Included	
Number of observations used	97,148		75,280		97,148	
R2	0.2535		0.2538		0.2541	

Table 10
Propensity Scoring Matching Analysis

Table 10, Panel A [Panel B] reports the Propensity score matching analysis using nearest and four-nearest matching methods for estimating the treatment effect of manipulation on innovation. First, the propensity scores for treatment (EOD or Infoleak manipulation) are computed using Probit regression of the model EOD_Dummy(t)/Infoleak_Dummy(t) = a + b*INNOV_PAT(t-1) + c*IPR_Index(t) + d*Enforcement_index(t) + e*Liquidity(t) + f'Controls. In Panel B, we exclude Liquidity(t) as an independent variable in this Probit regression.

Next, the nearest (four-nearest) neighbor propensity scoring methods match, within each country-industry-year strata, manipulated firms with control firms having the nearest (four-nearest) propensity scores as the manipulated firms. Both the propensity score matching methods discard treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls. The nearest (four-nearest) neighbor matching method matches without (with) replacement. Finally, the Average Treatment effect on the Treated (ATT) is the average difference between the manipulated and control firms of the change in the number (logarithm of the number) of patents in the year after and before the manipulation.

Panel A: Probit Regression Includes Liquidity(t) as an Independent Variable

Probit Regression

Dependent Variable	**EOD_Dummy(t)**		**Infoleak_Dummy(t)**	
INNOV_PAT(t-1)	-0.02231	***	-0.02803	***
IPR_Index(t)	0.15828	***	-0.15098	***
Enforcement_index(t)	-4.79175	***	1.44600	***
Liquidity(t)	0.03028	***	0.11987	***
MV_Decile(t)	0.03205	***	-0.01251	***
ROA(t)	0.24070	***	-0.01572	
PPETA(t)	-0.47437	***	-0.04168	
LEV(t)	-0.05950	**	0.23043	***
CAPEXTA(t)	0.32205	***	0.11448	
Q(t)	0.00130		-0.02262	***
LN_Firm_Age(t)	-0.14729	***	-0.02305	*
Constant	2.54262	***	-1.76371	***
Year and Firm fixed effects	Not Included		Not Included	
Industry fixed effects	Not Included		Not Included	
Number of observations used	90,272		90,272	
R2	0.0945		0.0945	

Average Treatment Effect on the Treated (ATT)

	EOD				INFOLEAK			
	(1) CHANGE_NUM_PAT		(2) CHANGE_LN_PAT		(3) CHANGE_NUM_PAT		(4) CHANGE_LN_PAT	
Nearest neighbor estimator								
ATT Difference-in-difference estimator	-0.21285		-0.01454		-0.04482		-0.01164	
Standard error	0.05233		0.00399		0.09350		0.00606	
t-statistics	-4.07	***	-3.65	***	-0.48		-1.92	*
Four-nearest neighbor estimator								
ATT Difference-in-difference estimator	-0.18912		-0.01397		-0.09412		-0.01347	
Standard error	0.05789		0.00449		0.09318		0.00603	
t-statistics	-3.27	***	-3.11	***	-1.01		-2.23	**

Panel B: Probit Regression Excludes Liquidity(t) as an Independent Variable

Probit Regression

Dependent variable	EOD_Dummy(t)		Infoleak_Dummy(t)	
INNOV_PAT(t-1)	0.00089		0.04465	***
IPR_Index(t)	0.21712	***	0.12074	***
Enforcement_index(t)	-5.26973	***	-0.90855	***
MV_Decile(t)	0.05612	***	0.07194	***
ROA(t)	0.31177	***	0.32888	***
PPETA(t)	-0.50833	***	-0.13913	***
LEV(t)	-0.00812		0.41383	***
CAPEXTA(t)	0.26327	***	-0.21964	**
Q(t)	-0.00379		-0.03380	***
LN_Firm_Age(t)	-0.11021	***	0.12455	***
Constant	2.37400	***	-2.18663	***
Year and Firm fixed effects	Not Included		Not Included	
Industry fixed effects	Not Included		Not Included	
Number of observations used	91,186		91,186	
R2	0.0906		0.0473	

Average Treatment Effect on the Treated (ATT)

	EOD				INFOLEAK			
	(1)		**(2)**		**(3)**		**(4)**	
	CHANGE_NUM_PAT		**CHANGE_LN_PAT**		**CHANGE_NUM_PAT**		**CHANGE_LN_PAT**	
Nearest neighbor estimator								
ATT Difference-in-difference estimator	-0.19418		-0.01130		-0.02257		-0.01037	
Standard error	0.05010		0.00392		0.08438		0.00595	
t-statistics	-3.88	***	-2.88	***	-0.27		-1.74	*
Four-nearest neighbor estimator								
ATT Difference-in-difference estimator	-0.17223		-0.01323		0.00007		-0.00983	
Standard error	0.05973		0.00450		0.08407		0.00586	
t-statistics	-2.88	***	-2.94	***	0		-1.68	*

Figure 1
Percentage of Change in Patent Applications/Citations and Manipulation

Figure 1 compares the percentage of change in the number of patent applications and patent citations from one period before the manipulation (t-1) to one period after the manipulation (t+1) for all the firms that have been manipulated and for those that have not experienced any end-of-day manipulation / information leakage.

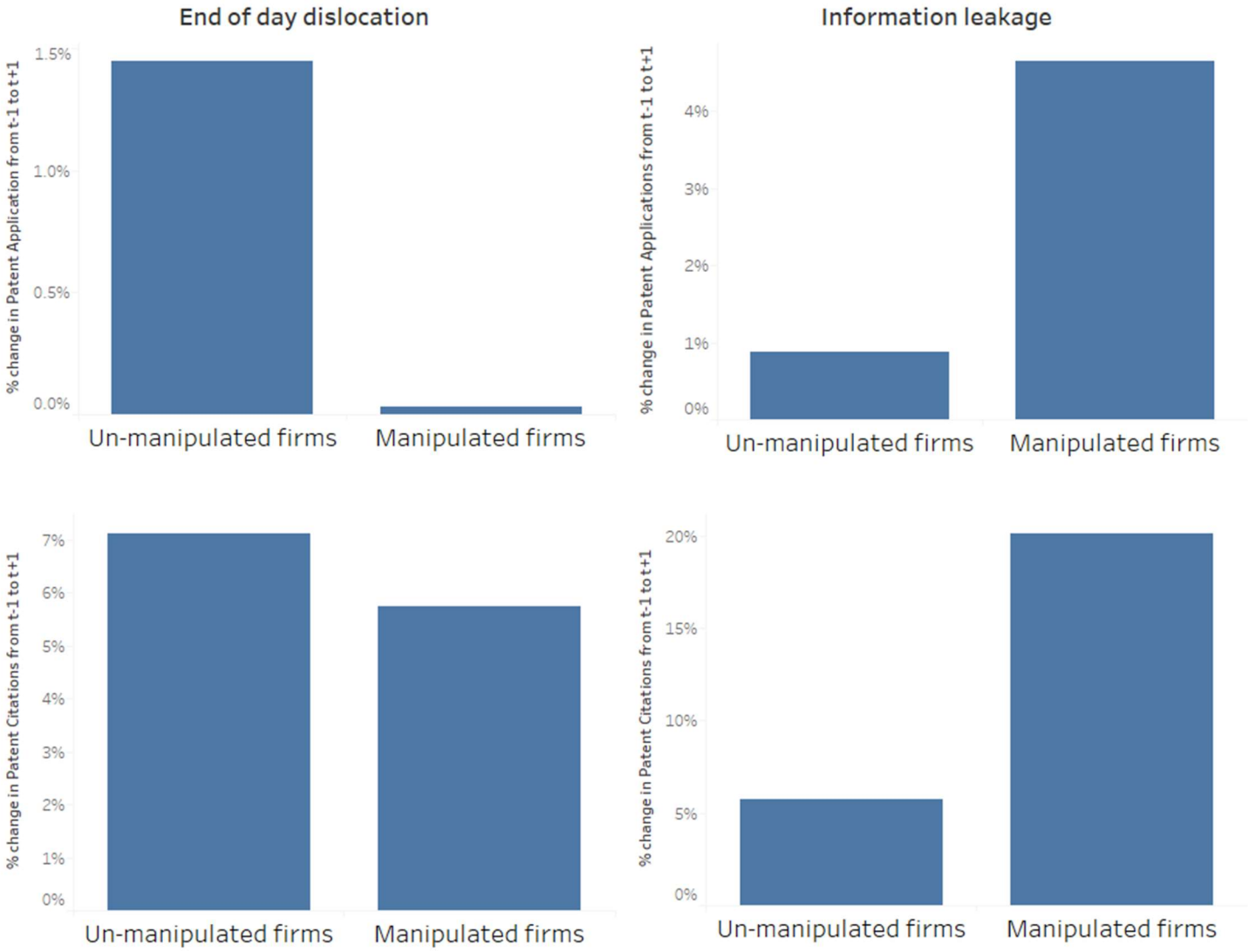


Figure 2.A
Percentage of Change in Patent Applications, Manipulation, and Intellectual Property Rights

Figure 2 compares the percentage of change in the number of patent applications from one period before the manipulation (t-1) to one period after the manipulation (t+1) for firms that have been manipulated and for those that have not experienced any end-of-day manipulation / information leakage, after splitting the sample into firms that belong to countries with a high level of intellectual property rights (IPR) and those with a low level of IPR.

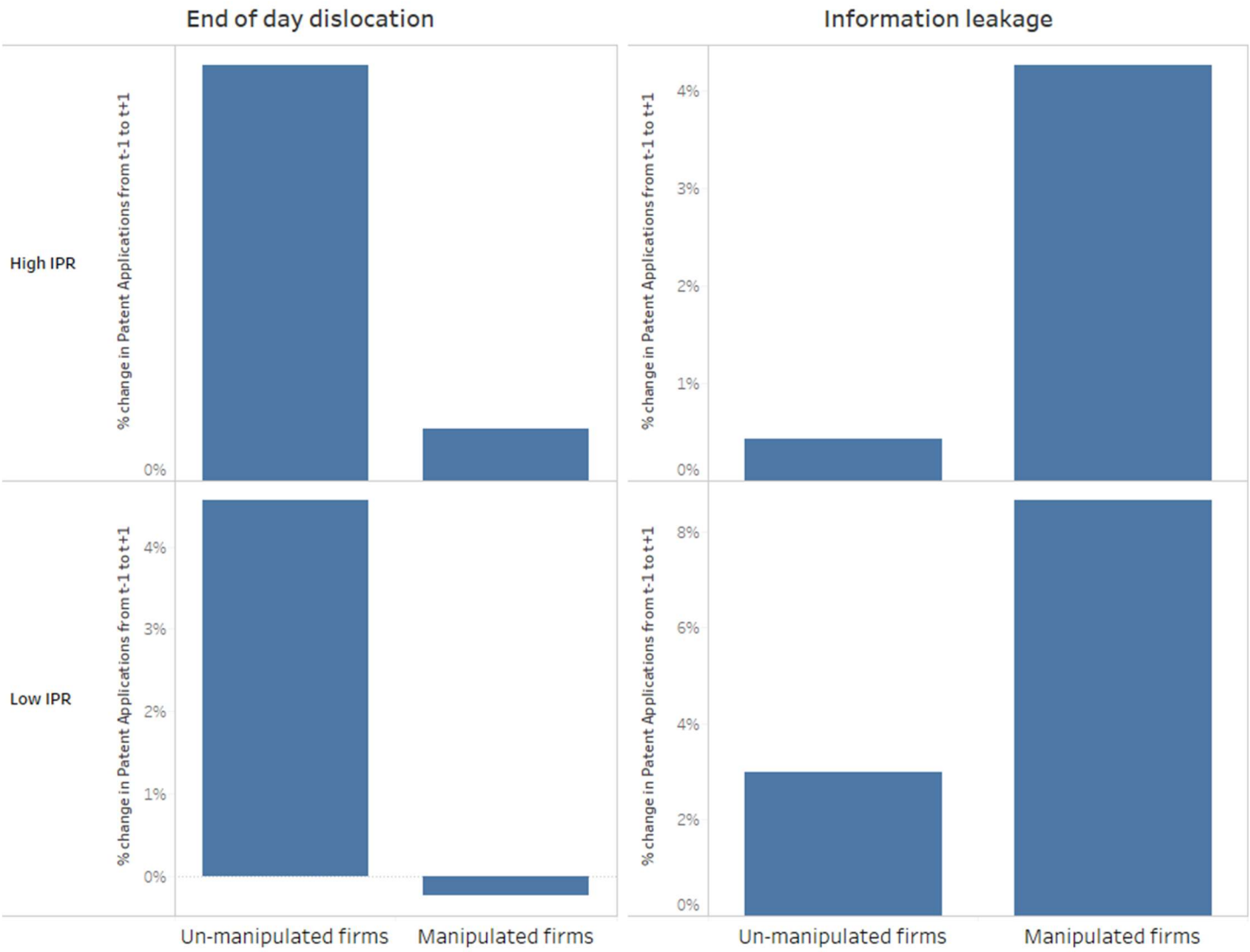


Figure 2.B
Percentage of Change in Patent Citations, Manipulation and Intellectual Property Rights

Figure 2 compares the percentage of change in the number of patent citations from one period before the manipulation (t-1) to one period after the manipulation (t+1) for firms that have been manipulated and for those that have not experienced any end-of-day manipulation / information leakage, after splitting the sample into firms that belong to countries with a high level of intellectual property rights (IPR) and those with a low level of IPR.

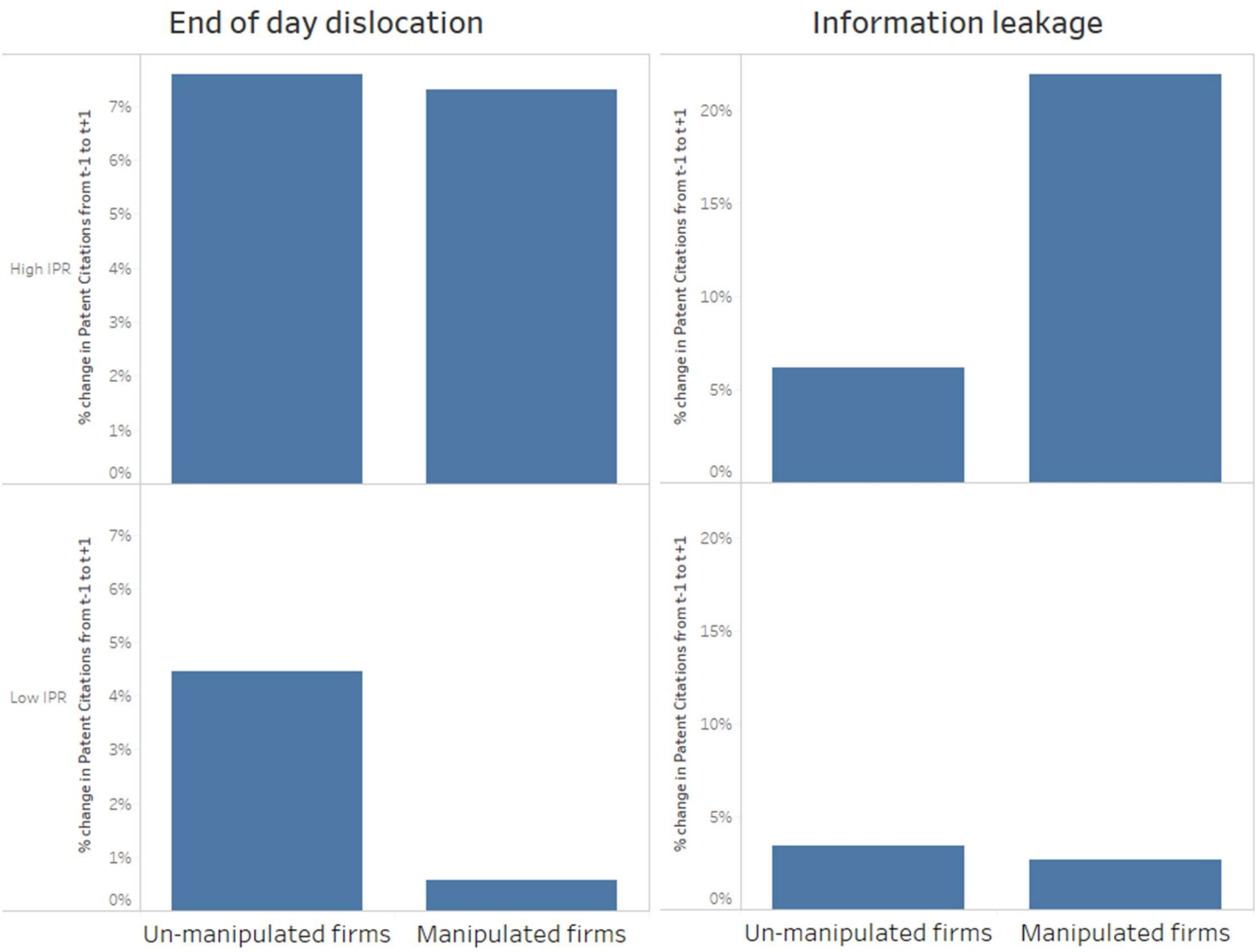


Figure 3.A
Percentage of Change in Patent Applications across Sectors and End-of-Day Dislocation

Figure 3.A compares the percentage of change in the number of patent applications from one period before the end-of-day manipulation (t-1) to one period after the manipulation (t+1) for firms that have been manipulated and for those that have not experienced any manipulation, after splitting the sample into sectors.

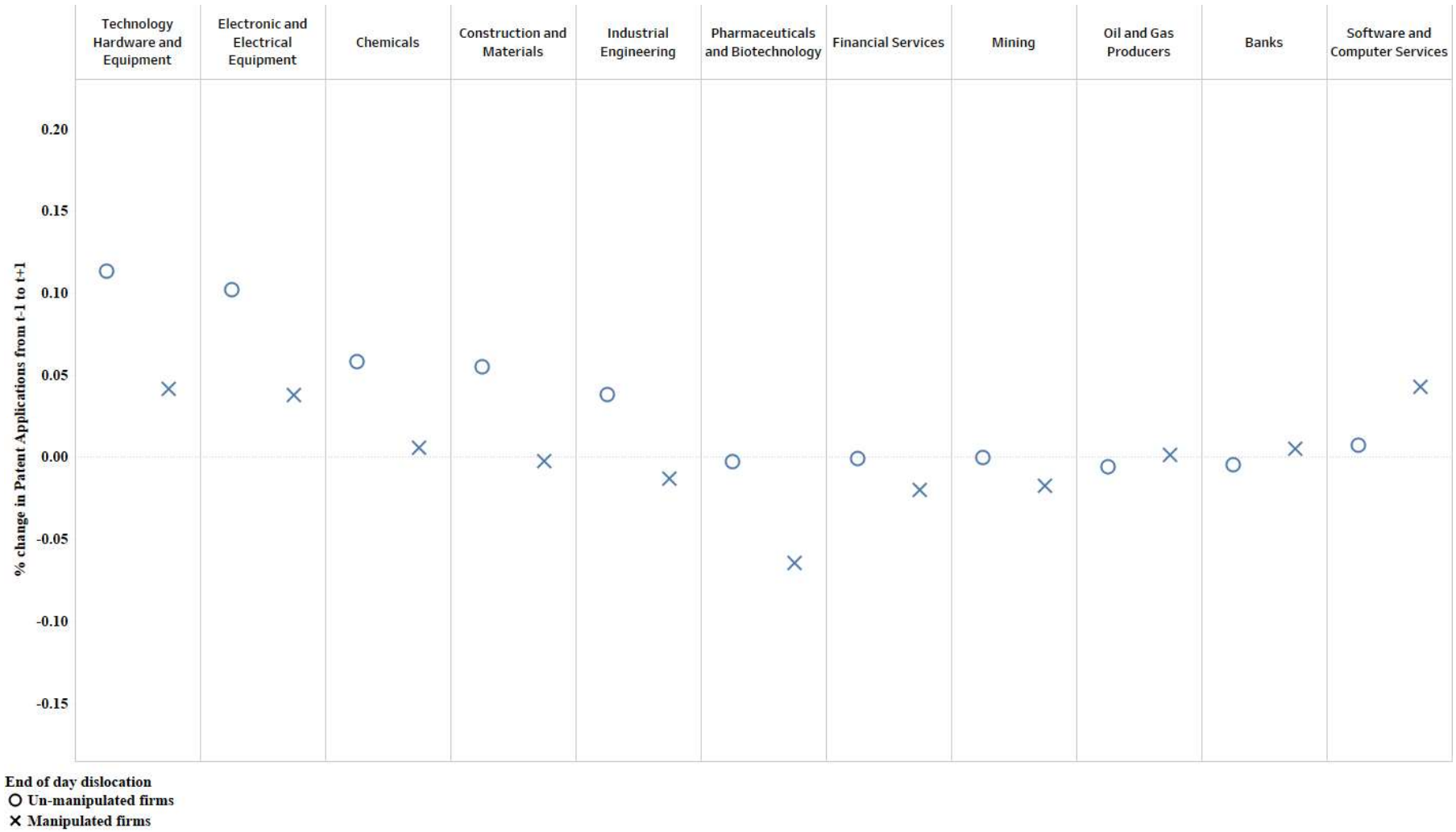
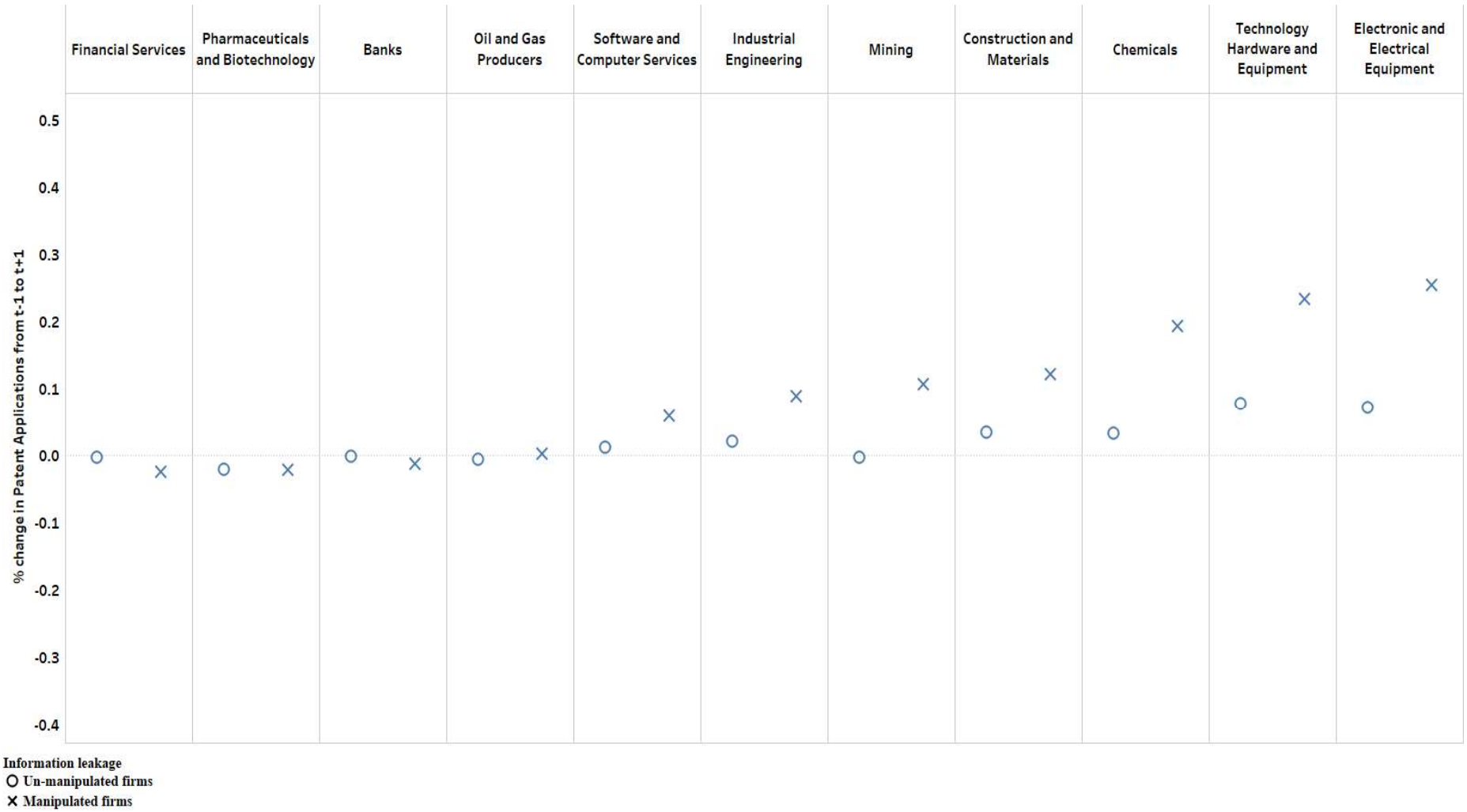


Figure 3.B
Percentage of Change in Patent Applications across Sectors and Information Leakage

Figure 3.B compares the percentage of change in the number of patent applications from one period before the information leakage manipulation (t-1) to one period after the manipulation (t+1) for firms that have been manipulated and for those that have not experienced any manipulation, after splitting the sample into sectors.



Appendix A
Replication of Tian et al. (2014)

Appendix A reports the pooled OLS regression results from replicating the Tian (2014) model INNOV_PAT(i,t+1) = a + b*Liquidity(t) + c'Controls(t) + YR(t) + Firm(i) + error(i,t) from 2003 to 2005 using the NBER patent data used by Tian (2014). Year fixed effects YR(i) and firm fixed effects Firm(i) are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

Dependent Variable	(1) INNOV_PAT(t+1)	
Liquidity(t)	0.01550	*
LN_MV(t)	0.05818	***
RDTA(t)	-0.40989	
ROA	-0.09381	
PPETA(t)	0.23270	
LEV(t)	-0.09802	
CAPEXTA(t)	-0.25895	
Q(t)	-0.02138	*
Year and Firm fixed effects	Included	
Number of observations used	11,885	
R2	0.6222	

Appendix B
Propensity Score Matching Analysis – Liquidity and Innovation

Appendix B reports the Propensity score matching analysis using nearest and four-nearest matching methods for estimating the ATT of Liquidity on innovation. First, the propensity scores are computed using Probit regression of the model Liquidity_treatment(t) = a + b1*EOD_Dummy(t) + b2*Infoleak_Dummy(t) + b3*INNOV_PAT(t-1) + c'Controls. Liquidity_treatement(t) is the treatment variable that takes a value of 1 when the firm is in the top tercile of change in liquidity and takes a value of 0 when the firm is in the bottom tercile of change in liquidity. Change in liquidity is measured as Liquidity(t+1) minus Liquidity(t-1). Next, the nearest (four-nearest) neighbor propensity scoring methods match the treated firms with control firms having the nearest (four-nearest) propensity scores as the treated firms. Both the propensity score matching methods discard treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls. The matching is done with replacement. Finally, the Average Treatment effect on the Treated (ATT) is the average difference between the treated and control firms of the change in the number (logarithm of the number) of patents in year after and before the treatment.

Panel A: Probit regression

Dependent variable	**Liquidity treatment(t)**	
EOD_Dummy(t)	-0.06258	***
Infoleak_Dummy(t)	0.01702	
INNOV_PAT(t-1)	0.05918	***
ROA	0.32250	***
PPETA(t)	-0.17926	***
LEV(t)	-0.07633	**
CAPEXTA(t)	0.24813	***
Q(t)	-0.00541	*
LN_Firm_Age(t)	0.11804	***
Constant	0.69849	***
Year and Firm fixed effects	Included	
Industry fixed effects	Included	
Number of observations used	48,477	
R2	0.3928	

Panel B: Average Treatment Effect on the Treated (ATT)

	Liquidity	
	(1)	**(2)**
	CHANGE_NUM_PAT	**CHANGE_LN_PAT**
Nearest neighbor estimator		
ATT Difference-in-difference estimator	0.23367	0.01319
Standard error	0.08314	0.01071
t-statistics	2.81	1.23
Four-nearest neighbor estimator		
ATT Difference-in-difference estimator	0.29638	0.02364
Standard error	0.06291	0.01041
t-statistics	4.71	2.27

ONLINE APPENDIX

In this Online Appendix, we show robustness to the subset of firms that only have a patent (Table A.1), the subset of firms excluding China (Table A.2), and the subset of a financial crisis versus a non-crisis period.

Table A.1 indicates that end-of-day manipulation negatively affects patents in all robustness checks. Information leakage negatively affects patents applied for but positively affects patents applied for and granted, suggesting that insiders take advantage of superior knowledge when then apply for a high-quality patent.

Table A.2 shows that the results are consistent with the exclusion of China from the sample.

Table A.3 shows that the results for end-of-day manipulation are robust in the subsamples including and excluding the crisis years. Table A.3 also shows that the results for information leakage hold in the non-crisis period but not in the crisis period. The intuition is as follows. At any time there is the negative impact of end-of-day manipulation and information leakage on innovation due to short-termism and poor focus for both types of manipulation. For information leakage, however, there is a counter force of insiders profiting more. In bad economic times that counter force is less profitable for insiders, and the risk of being caught is greater because regulators are especially diligent in crisis periods. Consequently, the former effect of short-termism associated with information leakage is stronger than the latter effect of expected profits during crisis periods.

Table A.1
Only Patenting Firms

Table A.1, Panel A [B] reports Firm Random Effects regression results, which include only firms with at least one patent of the model INNOV_PAT(i,t+1) [INNOV_CITE(i,t+1)] = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c1'Country_variable(Enforcement and IPR) + c2'Interaction_Country_variable_EOD + c3*Interaction_Liquidity_EOD + d'Controls + YR(t) + Sector(i) + error(i,t). INNOV_PAT(i,t+1) is the natural logarithm of one plus firm i's total number of patents filed in year t+1. INNOV_CITE(i,t+1) is the natural logarithm of one plus firm i's total number of citations received for patents filed in year t+1, which has been adjusted for truncation bias using the citation lag distribution. EOD_Dummy_First [EOD_Dummy_Subsequent] indicates if firm i has experienced end-of-day (EOD) dislocation in year t, under the condition that firm i never previously experienced [has previously experienced] EOD dislocation. Infoleak_Dummy indicates if firm i has experienced information leakage in year t. Similarly, Num_EOD_Cases_First, Num_EOD_Cases_Subsequent and Num_Infoleak_cases measure the number of times firm i has experienced EOD or Information leakage in year t. EOD_Dummy_Positive(t) indicates if firm i has experienced more positive EOD price dislocations than negative price dislocations in year t. Liquidity(t) is the natural logarithm of the inverse of the AMIHUD illiquidity variable. The Enforcement index is formed by adding the rule of law, efficiency of judiciary, risk of expropriation, repudiation of contracts by government, and corruption variables provided by LLSV and a scaling index between 0 and 1 (1998). The Intellectual Property Rights Index, IPR_Index, is obtained from the International Property Rights Index Report. Interaction_Liquidity_EOD, Interaction_Enforcement_EOD, and Interaction_IPR_EOD mixes the Liquidity(t), Enforcement_index(t), and IPR_Index(t), respectively, with the EOD_Dummy_Subsequent variable. Market value decile is (MV_Decile(t)), to which firm i belongs within each country-year; Return on Assets is (ROA(t)); Property plant and equity to total assets is (PPTA(t)), leverage measured as the book value of debt to book value of assets (LEV(t)); Capital expenditure to total assets is (CAPEXTA(t)); Tobin's Q is (Q(t)); and natural logarithm of one plus firm i's age, approximated by the number of years listed on Datastream (LN_Firm_Age(t)) are used as controls in all the models. Year fixed effects and industry fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

Panel A: Innovation Measured by INNOV_PAT(i,t+1)

	(1) Simple EOD Dummy		(2) EOD Dummy		(3) Number of EOD / Infoleak Cases	
EOD_Dummy(t)	-0.03751	***				
EOD_Dummy_First(t)			-0.00698			
EOD_Dummy_Subsequent(t)			-0.06540	***		
Infoleak_dummy(t)	-0.01393					
Num_EOD_Cases_First(t)					-0.00007	
Num_EOD_Cases_Subsequent(t)					-0.00480	***
Num_Infoleak_cases(t)			-0.01347		-0.00856	
Liquidity(t)	0.07656	***	0.07624	***	0.07603	***
IPR_Index	0.19115	***	0.19251	***	0.19211	***

MV_Decile(t)	0.03319	***	0.03339	***	0.03336	***
ROA(t)	-0.06583	***	-0.06592	***	-0.06584	***
PPETA(t)	0.14331	**	0.14338	**	0.14400	**
LEV(t)	0.09710	**	0.10004	**	0.09886	**
CAPEXTA(t)	-0.20342	**	-0.20872	**	-0.20686	**
Q(t)	-0.01689	***	-0.01700	***	-0.01688	***
LN_Firm_Age(t)	0.35544	***	0.35692	***	0.35760	***
Year fixed effects	Included		Included		Included	
Industry fixed effects	Included		Included		Included	
Number of observations used	30,892		30,892		30,892	
R2	0.3175		0.3173		0.3170	

Panel B: Innovation Measured by INNOV_CITE(i,t+1)

	(1) Simple EOD Dummy		**(2) EOD Dummy**		**(3) Number of EOD / Infoleak cases**	
EOD_Dummy(t)	-0.03934	***				
EOD_Dummy_First(t)			0.00986			
EOD_Dummy_Subsequent(t)			-0.07892	***		
Infoleak_dummy(t)	0.02311	**	0.02381	**		
Num_EOD_Cases_First(t)					-0.00245	
Num_EOD_Cases_Subsequent(t)					-0.01938	***
Num_Infoleak_cases(t)					0.02697	
Liquidity(t)	0.05672	***	0.05672	***	0.13082	***
Enforecement_index(t)						
IPR_Index	0.14123	***	0.13988	***	0.28216	***
Interaction_Enforcement_EOD						
Interaction_IPR_EOD						
Interaction_Liquidity_EOD						
MV_Decile(t)	0.02291	***	0.02317	***	0.07722	***
ROA(t)	-0.07131	***	-0.07150	***	-0.19019	***
PPETA(t)	0.03006		0.03054		0.17811	
LEV(t)	0.00683		0.00946		-0.08074	
CAPEXTA(t)	-0.19207	***	-0.19465	***	-0.34583	
Q(t)	-0.00942	***	-0.00946	***	-0.02600	***
LN_Firm_Age(t)	0.23147	***	0.23443	***	0.30498	***
Year fixed effects	Included		Included		Included	
Industry fixed effects	Included		Included		Included	
Number of observations used	97,148		97,148		90,272	
R2	0.2309		0.2305		0.2750	

Table A.2
Excluding China

Table A.2, Panel A [B] reports Firm Random Effects regression results, excluding China, of the model INNOV_PAT(i,t+1) [INNOV_CITE(i,t+1)] = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c1'Country_variable(Enforcement and IPR) + c2'Interaction_Country_variable_EOD + c3*Interaction_Liquidity_EOD + d'Controls + YR(t) + Sector(i) + error(i,t). INNOV_PAT(i,t+1) is the natural logarithm of one plus firm i's total number of patents filed in year t+1. INNOV_CITE(i,t+1) is the natural logarithm of one plus firm i's total number of citations received for patents filed in year t+1, which has been adjusted for truncation bias using the citation lag distribution. EOD_Dummy_First [EOD_Dummy_Subsequent] indicates if firm i has experienced end-of-day (EOD) dislocation in year t, under the condition that firm i never previously experienced [has previously experienced] EOD dislocation. Infoleak_Dummy indicates if firm i has experienced information leakage in year t. Similarly, Num_EOD_Cases_First, Num_EOD_Cases_Subsequent, and Num_Infoleak_cases measure the number of times firm i has experienced EOD or Information leakage in year t. EOD_Dummy_Positive(t) indicates if firm i has experienced more positive EOD price dislocations than negative price dislocations in year t. Liquidity(t) is the natural logarithm of the inverse of the AMIHUD illiquidity variable. The Enforcement_index is formed by adding the rule of law, efficiency of judiciary, risk of expropriation, repudiation of contracts by government, and corruption variables provided by LLSV, and scaling the index between 0 and 1 (1998). The Intellectual Property Rights Index, IPR_Index, is obtained from the International Property Rights Index Report. Interaction_Liquidity_EOD, Interaction_Enforcement_EOD, and Interaction_IPR_EOD mixes the Liquidity(t), Enforcement_index(t), and the IPR_Index(t), respectively, with the EOD_Dummy_Subsequent variable. The market value decile is (MV_Decile(t)), to which firm i belongs within each country-year. Return on Assets is (ROA(t)); Property plant and equity to total assets is (PPTA(t)), leverage measured as the book value of debt to book value of assets (LEV(t)); Capital expenditure to total assets is (CAPEXTA(t)); Tobin's Q is (Q(t)); the natural logarithm of one plus firm i's age is (LN_Firm_Age(t)), approximated by the number of years listed on Datastream, used as controls in all the models. Year fixed effects and industry fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

Panel A: Innovation Measured by INNOV_PAT(i,t+1)

	(1) Simple EOD Dummy		(2) EOD Dummy		(3) Number of EOD / Infoleak cases	
EOD_Dummy(t)	-0.00930	***				
EOD_Dummy_First(t)			0.00107			
EOD_Dummy_Subsequent(t)			-0.01796	***		
Infoleak_dummy(t)	-0.00616		-0.00601			
Num_EOD_Cases_First(t)					0.00047	
Num_EOD_Cases_Subsequent(t)					-0.00126	***
Num_Infoleak_cases(t)					-0.00365	
Liquidity(t)	0.02414	***	0.02413	***	0.02398	***
Enforecement_index						
IPR_Index	0.08775	***	0.08822	***	0.08841	***
Interaction_Enforcement_EOD						

Interaction_IPR_EOD						
Interaction_Liquidity_EOD						
MV_Decile(t)	0.00680	***	0.00686	***	0.00686	***
ROA(t)	-0.01865	***	-0.01872	***	-0.01871	***
PPETA(t)	0.01283		0.01296		0.01288	
LEV(t)	0.02487	**	0.02554	**	0.02536	**
CAPEXTA(t)	-0.05726	***	-0.05785	***	-0.05741	***
Q(t)	-0.00415	***	-0.00416	***	-0.00414	***
LN_Firm_Age(t)	0.30249	***	0.30305	***	0.30333	***
Year fixed effects	Included		Included		Included	
Industry fixed effects	Included		Included		Included	
Number of observations used	90,272		90,272		90,272	
R2	0.2507		0.2509		0.2507	

Panel B: Innovation Measured by INNOV_CITE(i,t+1)

	(1) Simple EOD Dummy		**(2) EOD Dummy**		**(3) Number of EOD / Infoleak cases**	
EOD_Dummy(t)	-0.03934	***				
EOD_Dummy_First(t)			0.00986			
EOD_Dummy_Subsequent(t)			-0.07892	***		
Infoleak_dummy(t)	0.02311	**	0.02381	**		
Num_EOD_Cases_First(t)					0.00136	
Num_EOD_Cases_Subsequent(t)					-0.00494	***
Num_Infoleak_cases(t)					0.01951	**
Liquidity(t)	0.05672	***	0.05672	***	0.05634	***
Enforecement_index						
IPR_Index	0.14123	***	0.13988	***	0.14123	***
Interaction_Enforcement_EOD						
Interaction_IPR_EOD						
Interaction_Liquidity_EOD						
MV_Decile(t)	0.02291	***	0.02317	***	0.02305	***
ROA(t)	-0.07131	***	-0.07150	***	-0.07148	***
PPETA(t)	0.03006		0.03054		0.03059	
LEV(t)	0.00683		0.00946		0.00856	
CAPEXTA(t)	-0.19207	***	-0.19465	***	-0.19302	***
Q(t)	-0.00942	***	-0.00946	***	-0.00941	***
LN_Firm_Age(t)	0.23147	***	0.23443	***	0.23476	***
Year fixed effects	Included		Included		Included	
Industry fixed effects	Included		Included		Included	
Number of observations used	90,272		90,272		90,272	
R2	0.2309		0.2305		0.2750	

Table A.3
Crisis Years – Patents Applied, Granted, and Adjusted

Table A.3 reports Firm Random Effects regression results of the model INNOV_PAT_GRNT_ADJ(i,t+1) = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c1'Country_variable(Enforcement and IPR) + c2'Interaction_Country_variable_EOD + c3*Interaction_Liquidity_EOD + d'Controls + YR(t) + Sector(i) + error(i,t). INNOV_PAT(i,t+1) is the natural logarithm of one plus firm i's total number of patents filed and granted, which have been adjusted for truncation bias, in year t+1. EOD_Dummy_First [EOD_Dummy_Subsequent] indicates if firm i has experienced end-of-day (EOD) dislocation in year t, under the condition that firm i never previously experienced [has previously experienced] EOD dislocation. Infoleak_Dummy indicates if firm i has experienced information leakage in year t. Liquidity(t) is the natural logarithm of the inverse of the AMIHUD illiquidity variable. The Intellectual Property Rights Index, IPR_Index, is obtained from the International Property Rights Index Report. Interaction_Liquidity_EOD mixes Liquidity(t) with the EOD_Dummy_Subsequent variable. Market value decile is (MV_Decile(t)), to which firm i belongs within each country-year; Return on Assets is (ROA(t)); Property plant and equity to total assets is (PPTA(t)); leverage measured as the book value of debt to book value of assets is (LEV(t)); Capital expenditure to total assets is (CAPEXTA(t)); Tobin's Q is (Q(t)); and natural logarithm of one plus firm i's age, approximated by the number of years listed on Datastream is (LN_Firm_Age(t)), used as controls in all the models. Year fixed effects and industry fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

Innovation Measured by INNOV_PAT_GRNT_ADJ(i,t+1)

	(1) Excluding Crisis Years		(2) Only Crisis Years	
EOD_Dummy_First(t)	0.00026		-0.03258	***
EOD_Dummy_Subsequent(t)	-0.00877	*	-0.03334	***
Infoleak_dummy(t)	0.01455	**	-0.00494	
Liquidity(t)	0.03657	***	0.03859	***
Interaction_Liquidity_EOD	0.00298	**	-0.00320	
IPR_Index	0.10623	***	0.09642	***
MV_Decile(t)	0.00331	**	0.02465	***
ROA(t)	-0.02182	***	-0.04653	***
PPETA(t)	-0.00321		0.01859	
LEV(t)	0.03316	***	-0.02585	
CAPEXTA(t)	-0.09876	***	-0.03247	
Q(t)	-0.00441	***	-0.00545	***
LN_Firm_Age(t)	0.17715	***	0.23327	***
Year fixed effects	Included		Included	
Industry fixed effects	Included		Included	
Number of observations used	70,752		26,396	
R2	0.2414		0.2593	