

Market Manipulation and Innovation

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Abstract

End-of-day price manipulation is associated short-termism of the firm's orientation, long-term harm to a firm's equity values, and commensurate reduced incentives for employees to innovate. Insider trading, by contrast, enables innovators to achieve exacerbated profits from innovation. Based on a comprehensive sample of all trading days and suspected end-of-day and insider trading events for all stocks from proprietary surveillance data from 9 countries over the years 2003-2010, we find evidence consistent with these real impacts of market manipulation on innovation.

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

JEL Classification: G14; G18; O30

1. Introduction

Pretty much without exception, financial market misconduct is viewed as being very costly to financial markets, and hence 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 et al., 1997, 1998, 2002, 2006) and individual level (Giannetti and Wang, 2014), (3) consequences in terms funds under management such as for hedge funds (Bollen and Pool, 2009) and mutual funds (Chapman et al., 2013), and (4) share price declines and legal penalties (Karpoff et al., 2008b; Karpoff and Lou, 2010; Dyck et al., 2010, 2014; Vismara et al., 2015). In this paper, we extend this line of literature by examining a fifth category not previously studied in the literature: the effect of financial market misconduct on innovation. We examine whether there is a link between financial market misconduct and firm patenting in a number of countries around the world.

Financial market misconduct comes in a variety of forms. Two of the most commonly observed (and hence commonly studied) forms of manipulation include insider trading (Allen and Gale, 1992; Allen and Gorton, 1992; Meulbroek, 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 then insiders 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 artificial level. End-of-day prices are used to determine the expiration value of derivative instruments and directors' options, price of seasoned equity issues, evaluate broker performance, compute net asset values of mutual funds, and compute stock indices (Aitken et al., 2015).¹

¹ See also Aggarwal and Wu (2006), Allen and Gale, (1992), Allen and Gorton (1992), Merrick et al. (2005), O'Hara (2001), O'Hara and Mendiola (2003), Peng and Röell (2013), Pirrong (1999, 2004), and Röell (1993).

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. 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 to explore radical new innovations because the rapid incorporation of good news into market prices creates incentives for short-termist behavior. 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. In net, therefore, predictions on a link between market manipulation and innovation are ambiguous in theory, and one must therefore look to data to ascertain the validity of a 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 9 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 that they are uniform without bias from differences in enforcement across firms and countries and over time. Also, suspected problems with a firm can be equally harmful to a firm as litigated problems in respect of 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 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 end of month, quarter and 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 things. The economic significance is such that the presence of end-of-day dislocation mitigates 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 in the subsequent year.

In contrast to the negative impact of dislocation on patents, information leakage has no effect on lower quality patents, but does have a positive impact on higher 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 the times of scandals 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 information leakage cases increases subsequent year's patent citations by 5.1%. Estimated differently, a 1-standard deviation increase in the number of 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 higher quality patents. The intuition is as follows. At any time there is 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 profiting more if you are an insider. 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.

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 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 the years 1994-2005.

Our analyses are distinct from these papers in a number of ways. First, in the Levine et al. paper 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 insider 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, that work does not examine whether or not a stock was manipulated, such as through insider trading or end-of-day manipulation. Surprisingly, unlike Fang et al. literature that 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 applying 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 than previously documented.

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

Our evidence has a number of important policy implications. Manipulation is common in society, 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 last section offers concluding remarks. Additional robustness tests are provided in the Appendices as well as an accompanying Online Appendix.

2. Economic Link between Market Manipulation and Innovation

Table I summarizes the economic causal link from market manipulation market in a microstructure sense to innovation. At first glance, the link between market microstructure and 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), so 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 in respect of a firm's long term economic outcomes

(Karpoff et al., 2008a,b, 2012), it is natural to focus on market manipulation and not merely stop at other microstructure properties of a firm's stock, such as its liquidity.

[TABLE I ABOUT HERE]

As discussed in the introduction, we consider here the two most common types of manipulation: end-of-day manipulation (massive share price movements in the last 15 minutes of trading one day and a reversal the next morning), and information leakage (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 instead were in reference to other firm events.

There are two panels in Table I. Panel A lists the first-order effects connecting manipulation to innovation. Manipulation damages long-term equity values (Aggarwal and Wu, 2006; Karpoff et al., 2008a,b; Dyck and Zingales, 2010; 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), shift the focus of a firm's management to short-termism and short-term pay structures (Peng and Röell, 2014). The shorter term focus of the firm is inconsistent with long-term innovation outcomes, as innovation requires a long-term horizon (Manso, 2011). Overall, therefore, in general we expect manipulation such as that of the form of end-of-day manipulation to negatively impact innovation.

There is a caveat in respect of 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). If so, 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, then 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 I 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), or 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 I in the next sections below.

3. Data and variable construction

3.1 Sample selection and data sources

The study covers 11 stock exchanges from nine countries during the period 2003 to 2010. The sample comprises Australia (Australian stock exchange), Canada (TSX Ventures), China

(Shanghai stock exchange), India (Bombay stock exchange and National Stock exchange of India), Japan (Tokyo stock exchange), New Zealand (New Zealand stock exchange), Singapore (Singapore stock exchange), Sweden (Stockholm stock exchange) and United States (NASDAQ and NYSE). Table II provides the definition and source of variables used in the study.

[TABLE II 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 on first publication and grant date, citation links, technological classifications, applicant and inventor identification for each patent application. The patent data is augmented using the ECOOM-EUROSTAT-EPO PATSTAT Person Augmented Table (EEE-PPAT) that 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 Capital Markets Cooperative Research Centre (CMCRC). The 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

Two measures of patenting activity are used in the study – the number of patent applications made by a firm in a year and 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 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. The application date of patents is used instead of 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 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) Then, 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 to 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 using 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 – the number of patents applied for and eventually granted ($INNOV_PAT_GRNT$) as well as the number of patents applied for and eventually granted that has been 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 is then computed using:

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

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 measure of innovation has its disadvantages. By using the number of patents we ignore differences between industries with regards to the intensity and duration of patents. We control for this by including industry and firm level controls for patent data. Using number of patent application 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 – End of day price dislocation (EOD) and 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 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 past 100 trading days benchmarking period. To be considered as 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 last trade price (P_t) and last available trade price 15 minutes before the continuous trading period ends (P_{t-15}) has to be bigger than 50%. $(P_{\text{auction or } P_t} - P_{t+1}) / (P_{\text{auction or } P_t} - P_{t-15}) \geq 50\%$.

To measure the Infoleakage alert, 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 deviations away from the mean abnormal return during the 250-day benchmarking period ending at 10 days before the news release. To be included in our sample, the stock must have at least 150 days' 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 examined 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 are 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 book value of total assets; asset tangibility, $PPETA(t)$, measured as the property, plant, and equipment expenditure divided by book value of total assets; leverage, $LEV(t)$, measured as book value of debt divided by book value of total assets; investment in fixed assets, $CAPEXTA(t)$, measured as Capital expenditures scaled by book value of total assets; firm age, $LN_FIRM_AGE(t)$, measured as natural logarithm of one plus 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 AMIHUUD measure of illiquidity. AMIHUUD is computed as follows:

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

Where A_{iy} is the AMIHUUD 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 available ratio in year y . A higher AMIHUUD value indicates higher level of illiquidity. Hence, we use the logarithm of the inverse of AMIHUUD as the measure of liquidity.

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

[TABLE III ABOUT HERE]

4. Univariate Tests

Table IV 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 IV is any firm-year observation where the EOD dummy or where 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 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 IV ABOUT HERE]

Table IV 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 in patent applications of 8.65% relative to 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 in patent applications [patent citations] of 4.25% [21.89%] relative to 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 I, II.A and II.B.

[FIGURES I AND II ABOUT HERE]

To complement the univariate statistics, in Figure III.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 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, and Software and Computer Services

at the 10% level, and insignificant in the other industries. Overall, the evidence in Figure III.A strongly supports Hypothesis 1.

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

Figure III.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 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 III.B strongly supports Hypothesis 2.

5. Multivariate tests

5.1. Base Model Specifications

Tables IV and V present the baseline regression estimates with pooled OLS and random effects, respectively.² Table VI differs from Table V 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 V and five regression models in Table VI are quite consistent and not sensitive to the inclusions of different sets of right-hand-side variables.

[TABLES IV AND V ABOUT HERE]

Tables IV and V 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

² 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.

firms that have experienced end-of-day dislocation have lower patents by 3.5% in the most conservative estimate (Table VI – Panel A, Model 3), and by 7.7% in the least conservative estimate (Table VI – Panel A, Model 4). Similarly, following end-of-day dislocation firms lower their citations by 15.4% in the most conservative estimate (Table VI – Panel B, Model 5) and by 25.1% in the least conservative estimate (Table VI – Panel B, Model 1). As an alternative specification in which we use a count of the number of dislocation cases (Table V Model 2 and Table VI 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 V – Panel A, Model 2) and a 1.9% reduction in the number of patents in the least conservative estimate (Table VI – Panel A, Model 2). Similarly, a 1-standard deviation increase in the number of dislocation cases is associated with a 5.9% reduction (Table V - Panel B, Model 2) 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 VI – Panel B, Model 2)

A 1-standard deviation increase in liquidity is associated with a 46% increase in number of patents and a 78.6% increase in the number of citations in the subsequent period (Table VI Model 1, and the other 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 9 countries over 2003-2010. In Appendix A, we study the U.S. only sample with 2003-2005 and the same data as Feng et al. (2014), and find results consistent with Tables IV and V 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 et 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 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 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, note Table VI – 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 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 IV and V 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 IV and V 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 number of patents (Table VI – Panel A, Models 4 and 5) and a 66% increase in the number of citations in the subsequent period (Table VI – Panel B, Models 4 and 5), which is consistent with a large 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 VI – Panel A, Model 3) and a 50.5% increase in the number of citations in the subsequent period (Table VI – 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 number of patent in the subsequent period (Table VI Model 1, and Models 2-5 are similar). A 1-standard deviation increase in leverage is associated with a 2.2% increase in number of patents in the subsequent period (Table VI Model 4, but this effect is insignificant in the Models 1 and 2). A 1-standard deviation increase in capital expenditures over assets is associated with a 2.1% decrease in number of patents in the subsequent period (Table VI Model 1, and Models 2-5 are similar). A 1-standard deviation increase in market/book is associated with a 2.5% decrease in number of patents in the subsequent period (Table VI Model 1, and Models 2-5 are similar). And finally, a 1-standard deviation increase in natural logarithm of the Firm age is associated

with a 47.5% increase in number of patents in the subsequent period (Table VI Model 1, and Models 2-5 are similar).

5.2. Robustness Checks

The remaining regressions 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. In Table VII 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 V and Table VI, with the economic significance of EOD manipulation slightly more pronounced. Model (2) excludes the global financial crisis period 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 VII 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 VII 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 subsequent year's patent citations by 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 subsequent year's patent citations by 5.1%. Estimated differently, a 1-standard deviation increase in the number of 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 subsequent year's patents by 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 subsequent year's patents applied for and granted by 6.51%.

Table VII Panel B shows stability of the negative effect of EOD manipulation on patenting for different types of clustering (Petersen, 2009) 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 VII Panels A and B are statistically significant in ways that are consistent with the Tables IV and V results. 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 VII ABOUT HERE]

Table VIII 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). But 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 VIII ABOUT HERE]

Table IX 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 IX ABOUT HERE]

Table X reports a 2SLS test of the impact of EOD manipulation and information leakage on innovation. The instrument used is the lagged patents in the industry, with the intuition that some industries may be subjected to different levels of manipulation. We show that the first stage results for the determinants of manipulation are sensitive to the inclusion/exclusion of the liquidity variable: lagged industry patents and liquidity are positively correlated. However, 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 than before, with a 1-standard deviation change in predicted EOD manipulation reducing future patenting by 37.9%. As before, with the 2SLS results there is no significant effect of information leakage on patents.

[TABLE X ABOUT HERE]

Table XI reports the results with propensity score matching. The data show a consistent and negative effect of EOD manipulation on innovation for 4 out of four tests in Models (1) and (2): nearest-neighbor matching for the change in 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 XI, 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 XI ABOUT HERE]

6. Limitations and Extensions

This paper focused on two types of manipulation: EOD manipulation and information leakage / suspected insider trading. There are many other types of manipulations, such as wash trades, option backdating, 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 this question of whether other types of manipulation have a stronger impact on manipulation.

This paper focused on 9 countries (Australia, Canada, China, India, Japan, New Zealand, Singapore, Sweden, and the United States) over 2003-2010. We showed the sensitivity of prior results on liquidity and innovation depends on the time period chosen. While we showed 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 9 countries spanning the years 2003-2010. The data indicate that end-of-day dislocation mitigates number of patents and the number of

citations received by patents due to the associated short-termism of the firm's orientation, 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 things.

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.

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Table I
Connecting market microstructure to innovation

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

	Market microstructure events		Predicted Impact on Innovation
	End of Day (EOD) Dislocation	Information leakage	
Panel A: First order effects			
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	Shorter term orientation leads to less innovation activity (Manso, 2011)
Overall Predicted Impact on Innovation	<u>Hypothesis 1:</u> EOD Dislocation lowers innovation	<u>Hypothesis 2:</u> 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 II
Variable definitions

Variable	Definition	Data source
INNOV_PAT(t+1)	Natural logarithm of one plus firm <i>i</i> 's total number of patents filed in year <i>t</i> +1.	PATSTAT
INNOV_CITE(t+1)	Natural logarithm of one plus firm <i>i</i> 's total number of citations received for patents filed in year <i>t</i> +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>i</i> 's total number of patents filed and eventually granted in the year <i>t</i> +1	PATSTAT
INNOV_PAT_GRNT_ADJ(t+1)	Natural logarithm of one plus firm <i>i</i> 's total number of patents filed and eventually granted in the year <i>t</i> +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 <i>t</i> .	PATSTAT
CHANGE_NUM_PAT	Change in number of patents computed as firm <i>i</i> 's total number of patents filed in the year <i>t</i> +1 minus firm <i>i</i> 's total number of patents filed in the year <i>t</i> -1	PATSTAT
CHANGE_LN_PAT	Natural logarithm one plus firm <i>i</i> 's total number of patents filed in the year <i>t</i> +1 minus the natural logarithm of one plus firm <i>i</i> 's total number of patents filed in the year <i>t</i> -1.	PATSTAT
EOD_Dummy	Indicates if a firm <i>i</i> has experienced end-of-day (EOD) dislocation in year <i>t</i> 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 last available trade price 15 minutes before the continuous trading period ends (P_{t-15}). For securities exchanges that have 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 past 100 trading days benchmarking period. To be considered as dislocation of EOD price case, at	CMCRC

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 last trade price (P_t) and last available trade price 15 minutes before the continuous trading period ends (P_{t-15}) has to be bigger than 50%. $(P_{\text{auction or } P_t} - P_{t+1}) / (P_{\text{auction or } P_t} - P_{t-15}) \geq 50\%$. Source: Capital Markets Cooperative Research Centre (CMCRC) and SMARTS, Inc.

EOD_Dummy_First(t)	Indicates if a 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 a 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 was never previously experienced EOD price dislocation until year t .	CMCRC
Num_EOD_Cases_Subsequent(t)	Number of times in year t 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 a firm i has experienced more positive EOD price dislocations than negative price dislocations in year t .	CMCRC
Infoleak_Dummy(t)	Indicates if a 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 deviations away from the mean abnormal return during the 250-day benchmarking period ending at	CMCRC

10 days before the news release. To be included in our sample, the stock must have at least 150 days' 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 examined 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_Infleak_Cases(t)	Number of times a firm has experienced information leakage in year t.	CMCRC
Strong(Weak)_EOD_First(t)	Indicates if a 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 a 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)_Infleak_First(t)	Indicates if a 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 trading days of a month.	CMCRC

Strong(Weak)_Infoleak_Subsequent(t)	Indicates if a firm <i>i</i> has experienced any information leakage in year <i>t</i> 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 <i>t</i> . 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 AMIHU illiquidity variable. The AMIHU illiquidity variable is computed as: $A_{ij} = \frac{1}{D_{iy}} \sum_{t=1}^{D_{iy}} \frac{ r_{it} }{Dvol_{it}}$ Where A_{iy} is the AMIHU measure of firm <i>i</i> in year <i>y</i> . R_{it} and $Dvol_{it}$ are daily return and daily dollar trading volume for stock <i>i</i> on day <i>t</i> . D_{iy} is the number of days with available ratio in year <i>y</i> . A higher AMIHU value indicates higher level of illiquidity. Hence, the logarithm of the inverse of AMIHU 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 the firm <i>i</i> belongs, within each country-year grouping, at the end of year <i>t</i> .	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 <i>t</i> .	Datastream
RDTA(t)	Research and development expenditures divided by book value of total assets measured at the end of fiscal year <i>t</i> , set to zero if missing.	Datastream
PPETA(t)	Property, plant & equipment divided by book value of total assets measured at the end of fiscal year <i>t</i>	Datastream
LEV(t)	Firm <i>i</i> 's leverage ratio, defined as book value of debt divided by book value of total assets measured at the end of fiscal year <i>t</i> .	Datastream
CAPEXTA(t)	Capital expenditures scaled by book value of total assets measured at the end of fiscal year <i>t</i> .	Datastream
Q(t)	Firm <i>i</i> 's market-to-book ratio during fiscal year <i>t</i> , 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>i</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 periods 2007 to 2010. For period 2003 to 2006 we used the oldest available index value from 2007.	Property Right Alliance
Enforcement_index	The 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 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 CMRC
Interaction_IPR_EOD(t)	Interaction variable computed as EOD_Dummy_Subsequent(t) x IPR_index(t)	Property rights alliance and CMRC

Table III
Summary Statistics

Table III reports the summary statistics for variables constructed using a sample of public firms from Australia, Canada, China, India, Japan, New Zealand, Singapore, Sweden and 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 IV
Comparison of percentage change in Number of patent applications

Table 3 compares the percentage change in 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 patents 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 patents 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	20,785	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 V
Pooled OLS Specification

Table V 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 a 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 a firm i has experienced information leakage in year t . Similarly, $Num_EOD_Cases_First$, $Num_EOD_Cases_Subsequent$ and $Num_Infoleak_cases$ measures the number of times a firm i has experienced EOD or Information leakage in year t . $EOD_Dummy_Positive(t)$ indicates if a 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 AMIHU illiquidity variable. $Interaction_Liquidity_EOD(t)$ interacts the $Liquidity(t)$ 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 to which firm i belongs within each country-year ($MV_Decile(t)$), Return on Assets ($ROA(t)$), Property plant and equity to total assets ($PPTA(t)$), leverage measured as the book value of debt to book value of assets ($LEV(t)$), Capital expenditure to total assets ($CAPEXTA(t)$), Tobins Q ($Q(t)$) 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. 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			97148

		97,148		97,148			
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 VI
Random Effects Specification

Table VI 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 a 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 a firm i has experienced information leakage in year t . Similarly, $Num_EOD_Cases_First$, $Num_EOD_Cases_Subsequent$ and $Num_Infoleak_cases$ measures the number of times a firm i has experienced EOD or Information leakage in year t . $EOD_Dummy_Positive(t)$ indicates if a 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 AMIHUDD illiquidity variable. $Enforcement_index$ 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 index to be between 0 and 1 (1998). Intellectual property rights index, IPR_Index , is obtained from the International property rights index report. $Interaction_Liquidity_EOD$, $Interaction_Enforcement_EOD$ and $Interaction_IPR_EOD$ interacts the $Liquidity(t)$, $Enforcement_index(t)$ and $IPR_Index(t)$ respectively with the $EOD_Dummy_Subsequent$ variable. Market value decile to which firm i belongs within each country-year ($MV_Decile(t)$), Return on Assets ($ROA(t)$), Property plant and equity to total assets ($PPTA(t)$), leverage measured as the book value of debt to book value of assets ($LEV(t)$), Capital expenditure to total assets ($CAPEXTA(t)$), Tobins Q ($Q(t)$) 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 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 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	***
Enforcement_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)		(2)		(3)		(4)		(5)		(6)	
	Simple		EOD		Number		Enforcement		IPR		EOD &	
	EOD		Dummy		of EOD		index		Index		Liquidity	
	Dummy				Cases							
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	***
Enforcement_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 VII
Robustness checks

Table VII 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.

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

In Panel B: Model (1) and (2) uses Patent application 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.

In 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
EOD_Dummy(t)	-0.00949 ***		
EOD_Dummy_First(t)		-0.00449	-0.00086
EOD_Dummy_Subsequent(t)		-0.01460 ***	-0.01001 ***
Infoleak_dummy(t)	0.01346 ***	0.01355 ***	0.01532 ***
IPR_Index(t)	0.10698 ***	0.10697 ***	0.10144 ***
Liquidity(t)	0.03141 ***	0.03133 ***	0.02817 ***
Interaction_Liquidity_EOD(t)	-0.00020	0.00039	0.00037
MV_Decile(t)	0.00334 ***	0.00338 ***	0.00514 ***
ROA(t)	-0.01989 ***	-0.01988 ***	-0.02090 ***
PPETA(t)	0.00433	0.00444	0.00829
LEV(t)	0.01182	0.01206	0.01698 *
CAPEXTA(t)	-0.08512 ***	-0.08535 ***	-0.09796 ***
Q(t)	-0.00424 ***	-0.00424 ***	-0.00439 ***
LN_Firm_Age(t)	0.19679 ***	0.19715 ***	0.17644 ***
Year fixed effects	Included	Included	Included
Industry fixed effects	Included	Included	Included
Number of observations used	97,148	97,148	97,148
R2	0.2377	0.2378	0.2357

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 VIII
Liquidity Deciles

Table VIII 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)		(2)		(3)		(4)
	Top 10th		Top 20th		Bottom 80th		Bottom 90th
	Decile of		Decile of		Decile of		Decile of
	Liquidity		Liquidity		Liquidity		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 IX
Manipulation on Month End Dates

Table IX 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 X 2SLS Specification

Table X reports the regression results of the 2SLS model that uses Average_industry-year_patents (t-1) as an instrument in the First stage regression. The second stage uses the OLS Pooled regression model $INNOV_PAT(i,t+1) = a + b1 * EOD_Dummy \text{ from First stage } (i,t) \setminus \text{Infoleak_Dummy from First stage } (i,t) + c' \text{Controls} + YR(t) + Firm(i) + error(i,t)$.

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: First Stage Logit regression includes Liquidity(t) as an independent variable

First stage Logit regression

Dependent variable	EOD_case_dummy	Infoleak_case_dummy
Instrument variable: Average_industry-year_patents(t-1)	-0.275239 ***	-0.0662803 ***
Controls used in Stage 2	Included	Included
Year fixed effects	Included	Included
Number of observations used	97,148	97,148
R2	0.041	0.1012

Second stage Pooled OLS regression with Firm fixed effects

Dependent variable is INNOV_PAT(i,t+1)

	(1) EOD manipulation	(2) Infoleak manipulation
EOD_Dummy from Stage 1 (t)	-1.43825 ***	
Infoleak_Dummy from Stage 1		0.00684
IPR_Index	0.03763 ***	0.08417 ***
Liquidity(t)	0.01665 ***	0.01214 ***
MV_Decile(t)	0.01679 ***	0.00233
ROA(t)	0.09280 ***	-0.00454
PPETA(t)	-0.19174 ***	0.00530
LEV(t)	0.04883 ***	0.02499 **
CAPEXTA(t)	0.21311 ***	-0.03451 **
Q(t)	-0.00238 ***	-0.00125 *
Year and firm fixed effects	Included	Included
Number of observations used	97,148	97,148
R2	0.9108	0.9106

Panel B: First Stage Logit regression includes Liquidity(t) as an independent variable

First stage Logit regression

Dependent variable	EOD_case_dummy	Infoleak_case_dummy
Instrument variable: Average_industry-year_patents(t-1)	-0.20863 ***	0.34556 ***
Controls used in Stage 2	Included	Included
Year fixed effects	Included	Included
Number of observations used	98,075	98,075
R2	0.0408	0.0698

Second stage

Dependent variable is INNOV_PAT(I,t+1)

	(1) EOD manipulation	(2) Infoleak manipulation
EOD_Dummy from Stage 1 (t)	-1.21643 ***	
Infoleak_Dummy from Stage 1		0.12211
IPR_Index(t)	0.04315 ***	0.08339 ***
Liquidity(t)	0.01168 ***	0.01215 ***
MV_Decile(t)	0.01857 ***	0.00110
ROA(t)	0.08201 ***	-0.00619
PPETA(t)	-0.16593 ***	0.00649
LEV(t)	0.05086 ***	0.01938
CAPEXTA(t)	0.16219 ***	-0.02722 *
Q(t)	-0.00312 ***	-0.00079
Year and Firm fixed effects	Included	Included
Number of observations used	97,148	97,148
R2	0.9107	0.9106

Table XI
Propensity scoring matching analysis

Table XI 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) neighbour 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) neighbour 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 number) of patents in 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
<i>Nearest neighbour estimator</i>				
ATT Difference-in-difference estimator	-0.21285	-0.01454	-0.04482	-0.01164
Standard error	0.05233	0.00399	0.09350	0.00606
<i>t</i> -statistics	-4.07 ***	-3.65 ***	-0.48	-1.92 *
<i>Four-nearest neighbour estimator</i>				
ATT Difference-in-difference estimator	-0.18912	-0.01397	-0.09412	-0.01347
Standard error	0.05789	0.00449	0.09318	0.00603
<i>t</i> -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
<i>Nearest neighbour estimator</i>				
ATT Difference-in-difference estimator	-0.19418	-0.01130	-0.02257	-0.01037
Standard error	0.05010	0.00392	0.08438	0.00595
<i>t</i> -statistics	-3.88 ***	-2.88 ***	-0.27	-1.74 *
<i>Four-nearest neighbour estimator</i>				
ATT Difference-in-difference estimator	-0.17223	-0.01323	0.00007	-0.00983
Standard error	0.05973	0.00450	0.08407	0.00586
<i>t</i> -statistics	-2.88 ***	-2.94 ***	0	-1.68 *

Figure I Percentage change in patent applications/citations and manipulation

Figure I compares the percentage 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.

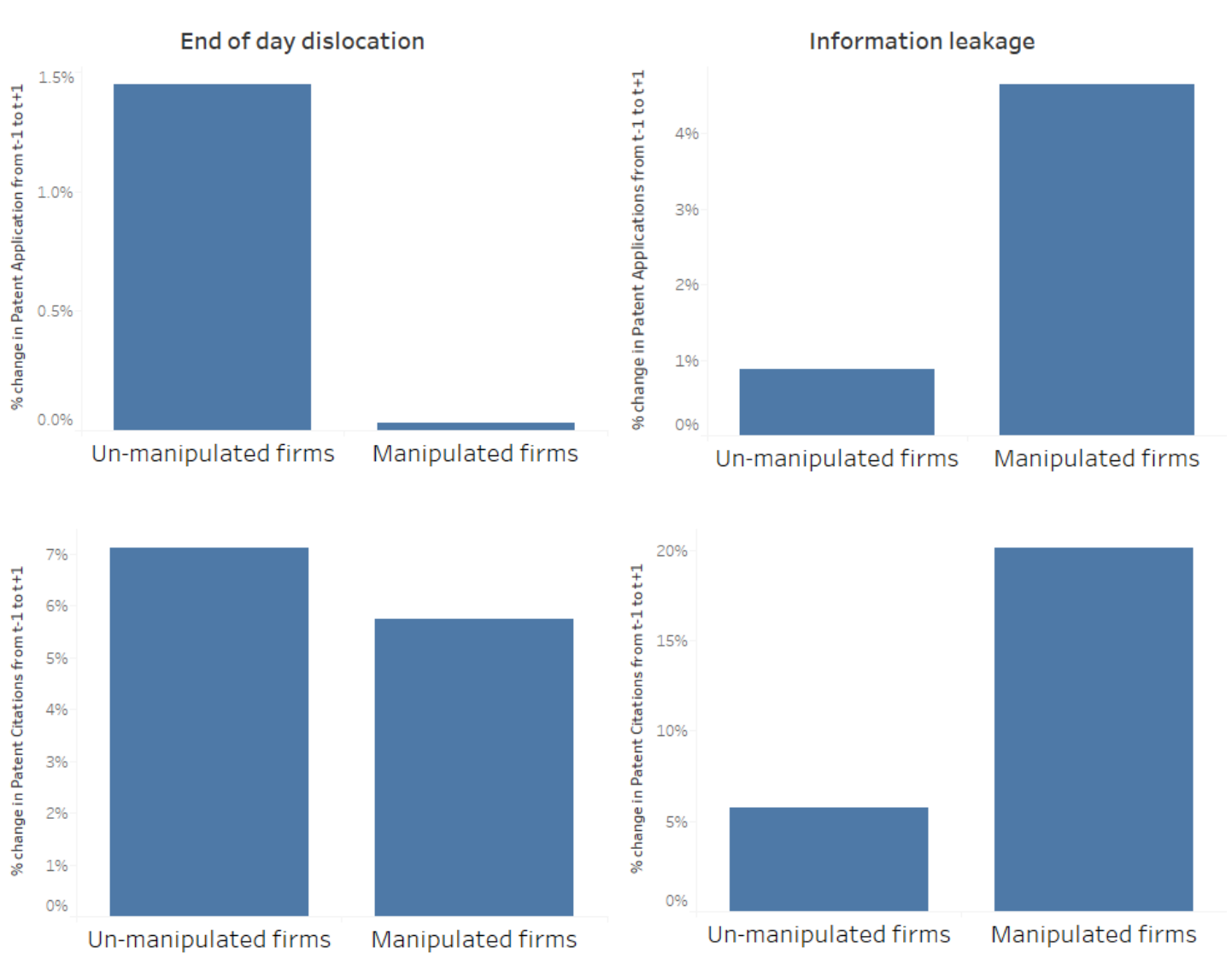


Figure II.A

Percentage change in patent applications, manipulation and intellectual property rights

Figure II compares the percentage change in 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 high level of intellectual property rights (IPR) and those that with a low level of IPR.

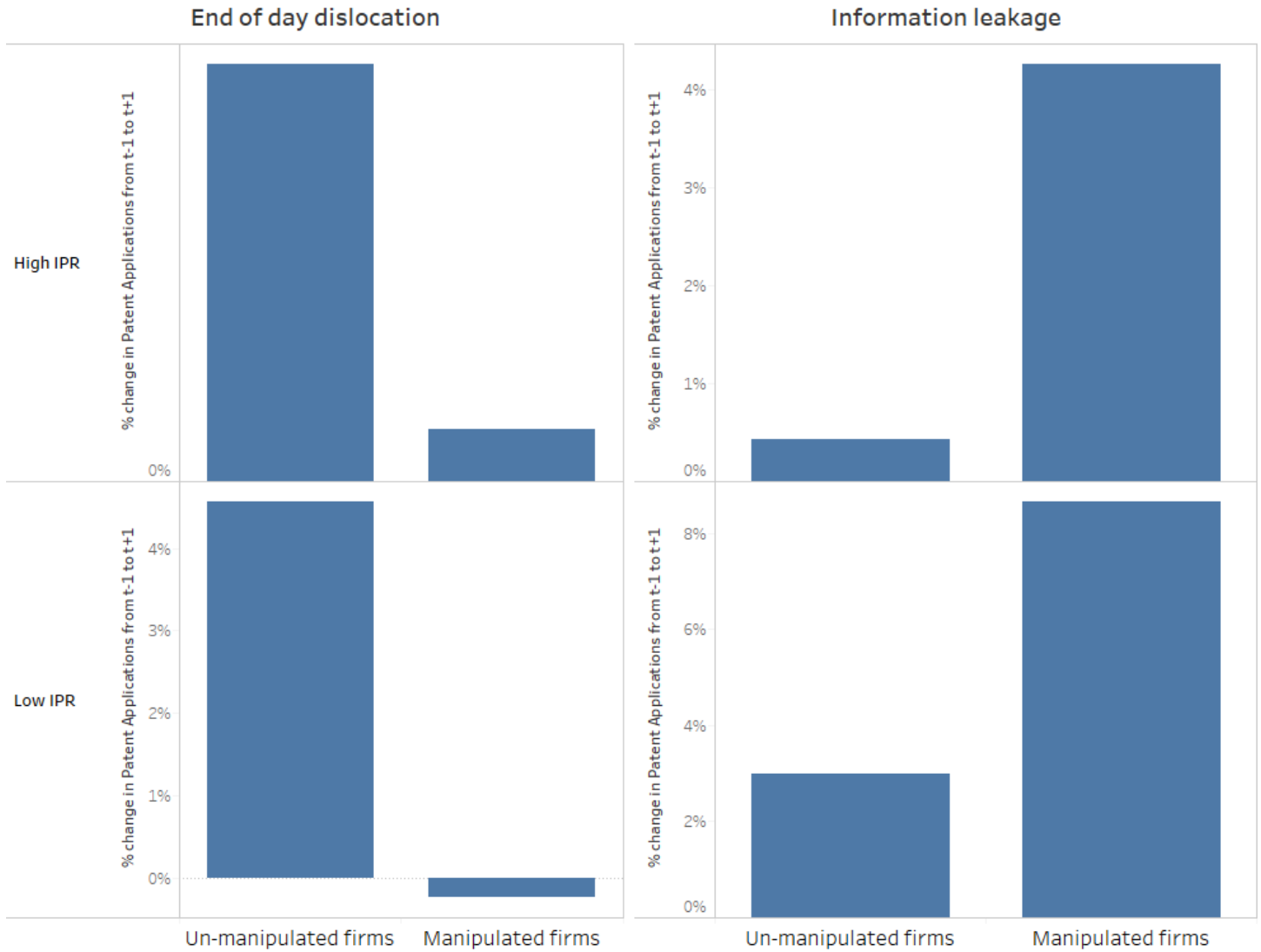


Figure II.B

Percentage change in patent citations, manipulation and intellectual property rights

Figure II compares the percentage change in 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 high level of intellectual property rights (IPR) and those that with a low level of IPR.

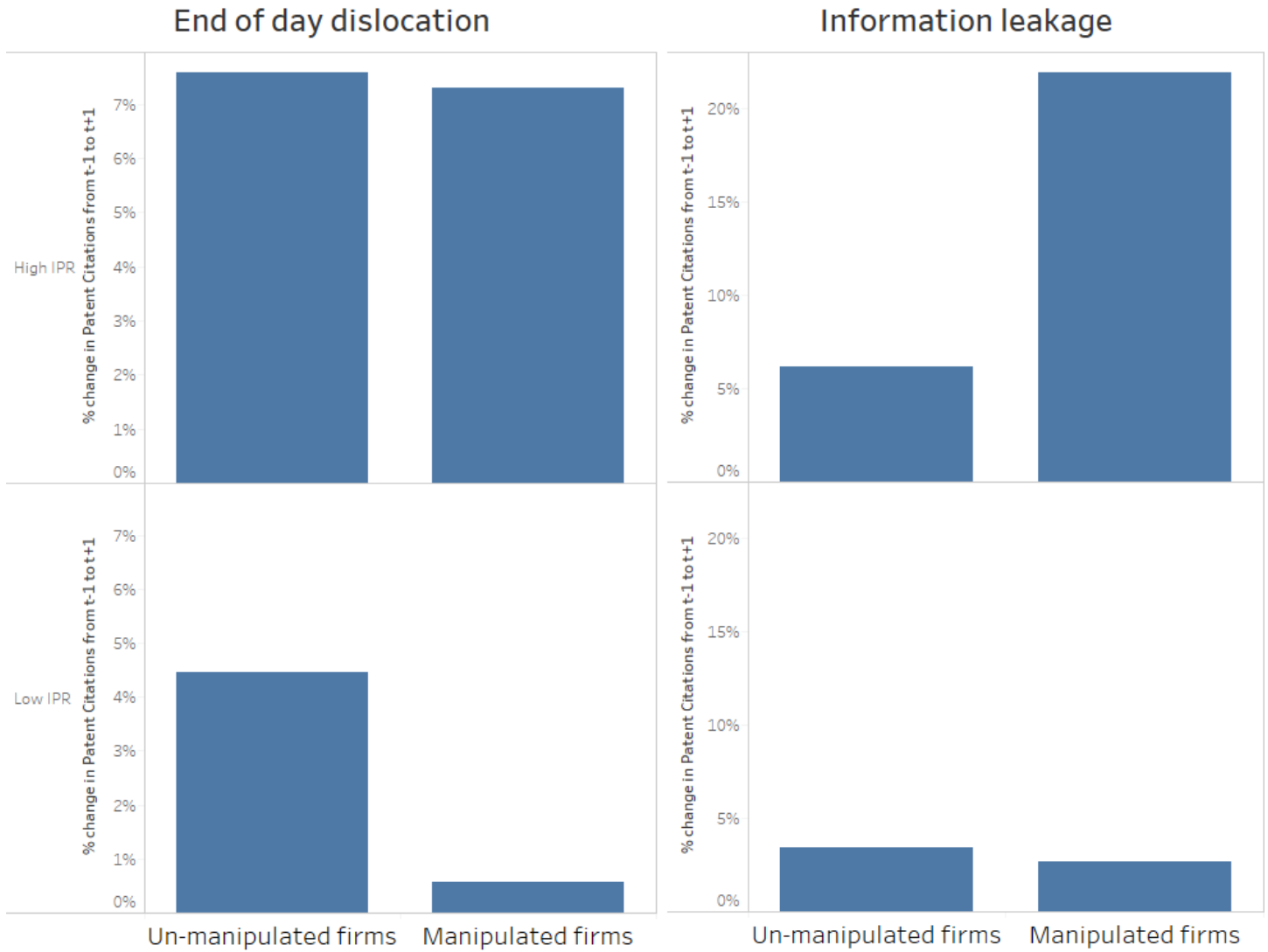


Figure III.A
Percentage change in patent applications across sectors and end of day dislocation

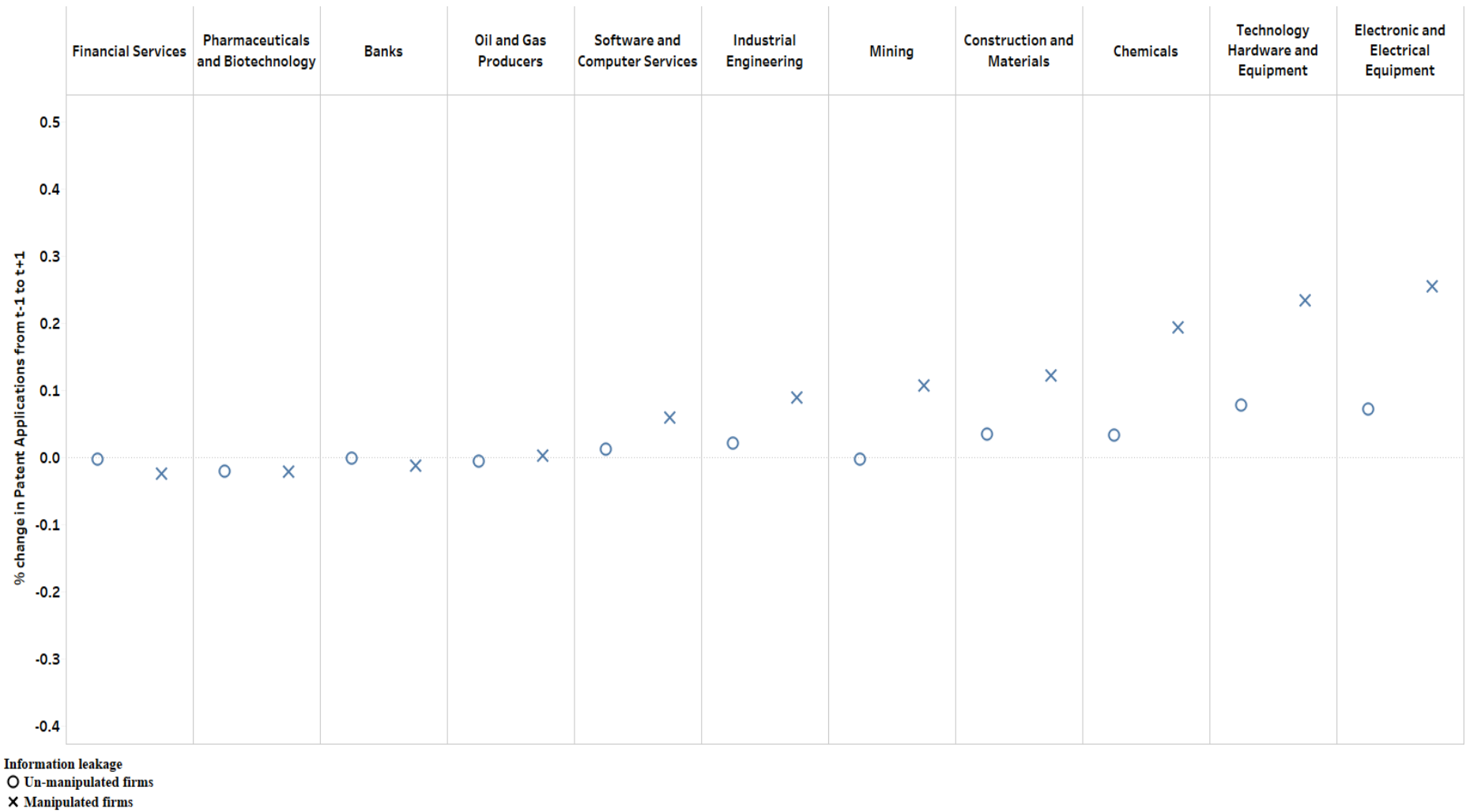
Figure III.A compares the percentage change in number of patent applications from one period before the end of day manipulation (t-1) to one period after the manipulation (t+1) for firms that have been manipulated and for those that have not experienced any manipulation, after splitting the sample into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



End of day dislocation
 ○ Un-manipulated firms
 × Manipulated firms

Figure III.B
Percentage change in patent applications across sectors and information leakage

Figure III.B compares the percentage change in 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 $INNOV_PAT(i,t+1) = a + b* Liquidity(t) + c* Controls(t) + YR(t) + Firm(i) + error(i,t)$ for the years 2003 to 2005 using the NBER patent data used by Tian (2014). Year fixed effects YR(i) and firm fixed effects Firm(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.

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 $Liquidity_treatment(t) = a + b1*EOD_Dummy(t) + b2*Infoleak_Dummy(t) + b3*INNOV_PAT(t-1) + c*Controls$. $Liquidity_treatment(t)$ 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) neighbour 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 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) CHANGE_NUM_PAT	(2) CHANGE_LN_PAT
<i>Nearest neighbour estimator</i>		
ATT Difference-in-difference estimator	0.23367	0.01319
Standard error	0.08314	0.01071
<i>t-statistics</i>	2.81	1.23
<i>Four-nearest neighbour estimator</i>		
ATT Difference-in-difference estimator	0.29638	0.02364
Standard error	0.06291	0.01041
<i>t-statistics</i>	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.I), the subset of firms excluding China (Table A.II), and the subset of financial crisis versus non-crisis period.

Table A.I indicates that end-of-day manipulation negatively affects patents in all robustness checks. Information leakage negatively 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.II shows that the results are consistent with the exclusion of China from the sample.

Table A.III shows that the results for end of day manipulation are robust in the subsamples including and excluding the crisis years. Table A.III 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 profiting more if you are an insider. 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. As such, the former effect of short-termism associated with information leakage is stronger than the latter effect of expected profits during crisis periods.

Table A.I
Only patenting firms

Table A.I Panel A [B] reports Firm Random Effects regression results, that includes 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 a 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 a firm i has experienced information leakage in year t . Similarly, $Num_EOD_Cases_First$, $Num_EOD_Cases_Subsequent$ and $Num_Infoleak_cases$ measures the number of times a firm i has experienced EOD or Information leakage in year t . $EOD_Dummy_Positive(t)$ indicates if a 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 AMIHU illiquidity variable. $Enforcement_index$ 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 index to be between 0 and 1 (1998). Intellectual property rights index, IPR_Index , is obtained from the International property rights index report. $Interaction_Liquidity_EOD$, $Interaction_Enforcement_EOD$ and $Interaction_IPR_EOD$ interacts the $Liquidity(t)$, $Enforcement_index(t)$ and $IPR_Index(t)$ respectively with the $EOD_Dummy_Subsequent$ variable. Market value decile to which firm i belongs within each country-year ($MV_Decile(t)$), Return on Assets ($ROA(t)$), Property plant and equity to total assets ($PPTA(t)$), leverage measured as the book value of debt to book value of assets ($LEV(t)$), Capital expenditure to total assets ($CAPEXTA(t)$), Tobins Q ($Q(t)$) 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 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 ***
Enforcement_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.II
Excluding China

Table A.II 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 a 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 a firm i has experienced information leakage in year t . Similarly, $Num_EOD_Cases_First$, $Num_EOD_Cases_Subsequent$ and $Num_Infoleak_cases$ measures the number of times a firm i has experienced EOD or Information leakage in year t . $EOD_Dummy_Positive(t)$ indicates if a 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. $Enforcement_index$ 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 index to be between 0 and 1 (1998). Intellectual property rights index, IPR_Index , is obtained from the International property rights index report. $Interaction_Liquidity_EOD$, $Interaction_Enforcement_EOD$ and $Interaction_IPR_EOD$ interacts the $Liquidity(t)$, $Enforcement_index(t)$ and $IPR_Index(t)$ respectively with the $EOD_Dummy_Subsequent$ variable. Market value decile to which firm i belongs within each country-year ($MV_Decile(t)$), Return on Assets ($ROA(t)$), Property plant and equity to total assets ($PPTA(t)$), leverage measured as the book value of debt to book value of assets ($LEV(t)$), Capital expenditure to total assets ($CAPEXTA(t)$), Tobins Q ($Q(t)$) 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 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
$EOD_Dummy(t)$	-0.00930 ***		
$EOD_Dummy_First(t)$		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 ***
$Enforcement_index$			
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
Enforcement_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.III
Crisis years – Patents applied, granted and adjusted

Table A.III reports Firm Random Effects regression results of the model $INNOV_PAT_GRNT_ADJ(i,t+1) = a + b1 \cdot EOD_Dummy_First(i, t) + b2 \cdot EOD_Dummy_Subsequent(i,t) + c \cdot Infoleak_Dummy(i,t) + c1 \cdot Country_variable(Enforcement\ and\ IPR) + c2 \cdot Interaction_Country_variable_EOD + c3 \cdot Interaction_Liquidity_EOD + d \cdot Controls + YR(t) + Sector(i) + error(i,t)$. $INNOV_PAT(i,t+1)$ is the natural logarithm of one plus firm i 's total number of patents filed and granted, that have been adjusted for truncation bias, in year $t+1$. EOD_Dummy_First [$EOD_Dummy_Subsequent$] indicates if a 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 a firm i has experienced information leakage in year t . $Liquidity(t)$ is the natural logarithm of the inverse of the AMIHU illiquidity variable. Intellectual property rights index, IPR_Index , is obtained from the International property rights index report. $Interaction_Liquidity_EOD$ interacts the $Liquidity(t)$ with the $EOD_Dummy_Subsequent$ variable. Market value decile to which firm i belongs within each country-year ($MV_Decile(t)$), Return on Assets ($ROA(t)$), Property plant and equity to total assets ($PPETA(t)$), leverage measured as the book value of debt to book value of assets ($LEV(t)$), Capital expenditure to total assets ($CAPEXTA(t)$), Tobins Q ($Q(t)$) 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.

Innovation measured by INNOV_PAT_GRNT_ADJ(i,t+1)			
	(1)		(2)
	Excluding crisis years		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