# Market Manipulation and Innovation

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# Market Manipulation and Innovation


**Abstract**

We study the impact of suspected market manipulation, including end-of-day manipulation and insider trading around information leakage events, on patents based on a sample of 9 countries spanning the years 2003-2010. The data indicate that end-of-day dislocation mitigates the number of patents and citations received, 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. Unlike prior literature that shows a negative relation between patenting and liquidity in the U.S. in an earlier time period, we observe a robust and significantly positive effect of liquidity on patenting in the U.S. and across the 9 countries in our sample over each of the 8 years studied. The positive effect of liquidity on innovation, however, is mitigated by the harmful 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. 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.



**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. Research on the consequences of financial market misconduct can be categorized into four types of papers: (1) managerial consequences such as salaries, termination, and jail terms (Karpoff et al., 2008a; Bereskin et al., 2014; Aharony et al., 2015), (2) stock market participation at the country level (La Porta at el., 1997, 1998, 2002, 2006) and individual level (Giannetti and Wang, 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; Meulbrook, 1992; Bebchuk and Fershtman, 1994; Agrawal and Cooper, 2015; Bernilie et al., 2015; Aitken et al., 2015b) and end-of-day manipulation (Comerton-Forde and Rydge, 2006; Comerton-Forde and Putnins, 2011, 2014; 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 (Comerton-Forde and Putnins, 2011, 2014).[1]

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 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. 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

[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 (2009), Pirrong (1999, 2004), and Röell (1993).

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. By contrast, we do not observe a significant effect of suspected insider trading around information announcements on subsequent patenting. 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.

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 inside trading laws were enforced, but there is variation in enforcement pertaining to a broader set of ways in which stocks may be manipulated. We find such variation to have a positive effect on manipulation, consistent with Levine et al.

Second, we examine whether or not there were actual events of apparent manipulation based on alerts (computer algorithms) examining historical microstructure data. To this end, our paper is distinct from the Fang et al. study which relates liquidity to innovation, 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 presents the data. Section 3 provides univariate tests of the relation between market manipulation and patents. Multivariate analyses are presented in section 4. Limitations and extensions are discussed in section 5. The last section offers concluding remarks. Additional robustness tests are provided in the Appendices.

## 2. Data and variable construction

### *2.1 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).

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.

Table 1 provides the definition and source of variables used in the study.

[TABLE I ABOUT HERE]

*2.2 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 75$^{th}$ 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:

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

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

Using patents as 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.

*2.3 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%. $(P_{auction\ or}\ P_{t\ -}\ P_{t+1})/(P_{auction\ or}\ P_t - P_{t-15}) \geq 50\%$.

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.

### *2.4 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 AMIHUD measure of illiquidity. AMIHUD is computed as follows:

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

Where $A_{iy}$ is the AMIHUD measure of firm i in year y. $R_{it}$ and $Dvol_{it}$ are daily return and daily dollar trading volume for stock i on day t. $D_{iy}$ is the number of days with available ratio in year y. A higher AMIHUD value indicates higher level of illiquidity. Hence, we use the logarithm of the inverse of AMIHUD as the measure of liquidity.

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

[TABLE II ABOUT HERE]

## 3. Univariate Tests

Table III presents univariate comparison of means tests. Panel A shows the comparison of the mean number of patents for firms that experienced end-of-day dislocation versus those that have not experienced end-of-day dislocation. The non-manipulation sample in Table III is any firm-year observation where the EOD dummy is equal to zero. Similar results (not presented) are obtained when measuring the mean levels of innovation using number of citations.

The data indicate that that prior to dislocation events, firms that have experienced dislocation have significantly higher numbers of patents (0.356) relative to those that have not experienced dislocation events (0.329) and this difference is statistically significant at the 1% level. The data further indicate that post-manipulation, firms that have experienced dislocation events are significantly more likely to have more patents (0.337) than those that have not (0.324), and this difference is statistically significant at the 5% level. The reduction in patents among those firms which have experienced dislocation from the pre- to –post-dislocation periods is statistically significant at the 1% level, as is the reduction in patents among those firms that have not experienced dislocation. But the comparative reduction in patents from the pre- to post-period is significantly larger among the firms that have experienced dislocation relative to those that have not, and that difference-in-differences is statistically significant at the 1% level.

[TABLE III ABOUT HERE]

Table III Panel B presents the univariate comparison tests for firms that have and have not experienced information leakage events. Consistent with Panel A for end-of-day dislocation, the data indicate that firms which have experienced information leakage have greater numbers of patents (0.657) relative to those that have not (0.305) in the pre-period, and this difference is significant at the 1% level. In the post period, firms that have experienced information leakage have a substantial reduction in patents (0.647), as do firms that have not experienced information leakage (0.299), but the comparative reduction in patents among the firms that experienced dislocation in the post period is substantially larger, and this difference-in-differences is statistically significant at the 1% level of significance.

Overall, the univariate tests are consistent with the view that firms are more likely to experience dislocation and information leakage if they have more patents, and the impact of dislocation and information leakage on patents is strongly negative and statistically significant. These effects are depicted graphically in Figure 1.

[FIGURE I ABOUT HERE]

## 4. Multivariate tests

### *4.1. Base Model Specifications*

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

[TABLES IV AND V ABOUT HERE]

[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.

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. The economic significance is such that firms that have experienced end-of-day dislocation have lower patents by 3.5% in the most conservative estimate (Table V – Panel A, Model 3), and by 7.7% in the least conservative estimate (Table V – Panel A, Model 4). Similarly, following end-of-day dislocation firms lower their citations by 15.4% in the most conservative estimate (Table V – Panel B, Model 5) and by 25.1% in the least conservative estimate (Table V – Panel B, Model 1). As an alternative specification in which we use a count of the number of dislocation cases (Table IV Model 2 and Table V 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 IV – Panel A, Model 2) and a 1.9% reduction in the number of patents in the least conservative estimate (Table V – Panel A, Model 2). Similarly, a 1-standard deviation increase in the number of dislocation cases is associated with a 5.9% reduction (Table IV - 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 V – 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 V 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 at al. do not examine whether or not a stock was manipulated, such as through insider trading or end-of-day manipulation. Appendix B performs further robustness tests of the relation between liquidity and innovation with propensity score matched analyses, and shows a consistent and positive effect of liquidity on innovation for 3 out of four tests: nearest-neighbor matching for the change in 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 V – 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 V – Panel A, Models 4 and 5 and a 66% increase in the number of citations in the subsequent period (Table V – 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 V – Panel A, Model 3) and a 50.5% increase in the number of citations in the subsequent period (Table V – 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 V 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 V 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 V 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 V 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 V Model 1, and Models 2-5 are similar).

*4.2. 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 VI 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 IV and Table V, 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 VI 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 VI Panel A, which shows a positive and significant effect for applied and granted patents, and applied and granted patents adjusted for truncation bias. 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. But again, this effect is not robust, as the effect is not significant without winsorizing in Model (6), and not significant in Models (1) and (2). By contrast, the negative effect of EOD manipulation is statistically significant and robust in all of the model specifications.

Table VI 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 VI 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 VI ABOUT HERE]

Table VII 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 $10^{th}$ and $20^{th}$ liquidity deciles, but not the bottom $80^{th}$ and $90^{th}$ 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, 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 VII ABOUT HERE]

Table VIII shows the results for the days on which EOD dislocation is more likely to be association 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 VIII ABOUT HERE]

Table IX 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 IX ABOUT HERE]

Table X 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 X, 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 X ABOUT HERE]

## 5. 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.

Finally, future research could study other measures of innovation apart from patent counts, as well as examine the quality of innovation. Those issues are beyond the scope of this paper with our international sample, but could be addressed in future studies.

## 6. 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 do not find a similar consistent negative effect of information leakage on patents. This difference is possibly due to the fact that insiders may have in some cases pronounced incentives to engage in insider trading associated with announcement of innovations. Future research could examine specific cases in more details, among other extensions related to those that we discussed in this paper.

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## Table I
## Variable definitions

| Variable | Definition | Data source |
|---|---|---|
| INNOV_PAT(t+1) | Natural logarithm of one plus firm *i*'s total number of patents filed in year *t*+1. | PATSTAT |
| INNOV_CITE(t+1) | Natural logarithm of one plus firm *i*'s total number of citations received for patents filed in year *t*+1. The number of citations has been adjusted for truncation bias using the citation lag distribution. | PATSTAT |
| INNOV_PAT_GRNT(t+1) | Natural logarithm of one plus firm *i*'s total number of patents filed and eventually granted in the year t+1 | PATSTAT |
| INNOV_PAT_GRNT_ADJ(t+1) | Natural logarithm of one plus firm *i*'s total number of patents filed and eventually granted in the year t+1, which has been adjusted for truncation bias using the grant lag distribution. | PATSTAT |
| Average_industry-year_patents(t-1) | The average INNOV_PAT(t-1) for an industry within each country, in the year t. | PATSTAT |
| CHANGE_NUM_PAT | Change in number of patents computed as firm *i's* total number of patents filed in the year t+1 minus firm *i's* total number of patents filed in the year t-1 | PATSTAT |
| CHANGE_LN_PAT | Natural logarithm one plus firm *i's* total number of patents filed in the year t+1 minus the natural logarithm of one plus firm *i's* total number of patents filed in the year t-1. | PATSTAT |
| EOD_Dummy | Indicates if a firm i has experienced end-of-day (EOD) dislocation in year t<br><br>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 least 50% of the price dislocation has to revert at open on the next trading day. Hence, the price | CMCRC |

| | | |
|---|---|---|
| | 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%. ($P_{auction\ or}$ $P_{t\ -}$ $P_{t+1}$)/( $P_{auction\ or}P_t$ - $P_{t-15}$ ) $\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.<br><br>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 10 days before the news release. To be included in our sample, the stock must have at least 150 days’ | CMCRC |

| | | |
|---|---|---|
| | 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_Infoleak_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)_Infoleak_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 has experienced any information leakage in year t during the days more likely to experience manipulation (except on days more | CMCRC |

| | | |
|---|---|---|
| | 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. | |
| Liquidity(t) | Denotes the natural logarithm of the inverse of the AMIHUD illiquidity variable. The AMIHUD illiquidity variable is computed as: $$A_{ij} = \frac{1}{D_{iy}} \sum_{i=1}^{D_{iy}} \frac{\lvert r_{it} \rvert}{Dvol_{it}}$$ Where $A_{iy}$ is the AMIHUD measure of firm i in year y. $R_{it}$ and $Dvol_{it}$ are daily return and daily dollar trading volume for stock i on day t. $D_{iy}$ is the number od days with available ratio in year y. A higher AMIHUD value indicates higher level of illiquidity. Hence, the logarithm of the inverse of AMIHUD would be a measure of liquidity rather than illiquidity. | Datastream |
| MV_Decile(t) | Market value decile variable takes the value of 1 to 10 based on the market value decile to which the firm i belongs, within each country-year grouping, at the end of year t. | Datastream |
| ROA(t) | Return on assets defined as the Income before extraordinary items divided by book value of total assets, measured at the end of fiscal year t. | Datastream |
| RDTA(t) | Research and development expenditures divided by book value of total assets measured at the end of fiscal year t, set to zero if missing. | Datastream |
| PPETA(t) | Property, plant & equipment divided by book value of total assets measured at the end of fiscal year t | Datastream |
| LEV(t) | Firm i's leverage ratio, defined as book value of debt divided by book value of total assets measured at the end of fiscal year t. | Datastream |
| CAPEXTA(t) | Capital expenditures scaled by book value of total assets measured at the end of fiscal year t. | Datastream |
| Q(t) | Firm i's market-to-book ratio during fiscal year t, calculated as the market value of equity plus book value of debt divided by book value of assets. | Datastream |
| LN_Firm_Age(t) | Natural logarithm of one plus firm *i*'s age, approximated by the number of years listed on Datastream. | Datastream |

| | | |
|---|---|---|
| IPR_Index(t) | Intellectual property rights index obtained from the International property rights index report published from 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 CMCRC |
| Interaction_IPR_EOD(t) | Interaction variable computed as EOD_Dummy_Subsequent(t) x IPR_index(t) | Property rights alliance and CMCRC |

# Table II
# Summary Statistics

Table 2 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 III
# Comparison of Means

Table 3(a) compares the mean INNOV_PAT(t+1) to the mean INNOV_PAT(t-1) for both firms that have been experienced end of day price manipulation and those that have not experienced end of day price manipulation. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

Table 3(a): Mean INNOV_PAT pre and post EOD manipulation

| | N | Pre-manipulation [A] | Post-manipulation [B] | Comparison of means [B-A] |
|---|---|---|---|---|
| Firms that have been manipulated [C] | 25,846 | 0.3556 | 0.3369 | **-0.0187*** ** |
| Firms that have not been manipulated [D] | 105,283 | 0.3288 | 0.3240 | **-0.0048*** ** |
| Comparison of means [C-D] | | **0.0268*** ** | **0.0129** ** | |
| Difference in Differences ( [C-D] for [B-A] ) | | | | **-0.0139*** ** |

Table 3(b) compares the mean INNOV_PAT(t+1) to the mean INNOV_PAT(t-1) for both firms that have experienced information leakage and those that have not experienced information leakage. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

Table 3(b): Mean INNOV_PAT pre and post Information Leakage manipulation

| | N | Pre-manipulation [A] | Post-manipulation [B] | Comparison of means [B-A] |
|---|---|---|---|---|
| Firms that have experienced information leakage [C] | 10,350 | 0.6753 | 0.6472 | **-0.0281*** ** |
| Firms that have not experienced information leakage [D] | 120,779 | 0.3048 | 0.2991 | **-0.0057*** ** |
| Comparison of means [C-D] | | **0.3704*** ** | **0.3481*** ** | |
| Difference in Differences ( [C-D] for [B-A] ) | | | | **-0.0223*** ** |

# Table IV
# Pooled OLS Specification

Table 4 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 AMIHUD 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)), Tobin's 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) | |
|---|---|---|---|---|---|---|
| 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) | -0.00622 | | - | | -0.00624 | |
| Num_EOD_Cases_First(t) | - | | 0.00061 | | - | |
| Num_EOD_Cases_Subsequent(t) | - | | -0.00122 | *** | - | |
| Num_Infoleak_cases(t) | - | | -0.00372 | | - | |
| Liquidity(t) | 0.08598 | *** | 0.08624 | *** | 0.01266 | *** |
| Interaction_Liquidity_EOD (t) | - | | - | | -0.00267 | ** |
| IPR_index(t) | 0.01228 | *** | 0.01218 | *** | 0.08594 | *** |
| MV_Decile(t) | 0.00258 | * | 0.00259 | * | 0.00256 | * |
| ROA(t) | -0.00483 | | -0.00482 | | -0.00498 | |
| PPETA(t) | 0.00547 | | 0.00535 | | 0.00537 | |
| LEV(t) | 0.02618 | ** | 0.02599 | ** | 0.02637 | ** |
| CAPEXTA(t) | -0.03519 | ** | -0.03475 | ** | -0.03553 | ** |
| Q(t) | -0.00135 | * | -0.00134 | * | -0.00136 | * |
| Year and Firm fixed effects | Included | | Included | | Included | |
| Sector fixed effects | Included | | Included | | Included | |
| | | | | | | |
| Number of observations used | 97,148 | | 97,148 | | 97148 | |
| Adjusted R2 | 0.91060 | | 0.91060 | | 0.9106 | |

| Panel B: Innovation measured by INNOV_CITE(i, t+1) | | | | | | |
|---|---|---|---|---|---|---|
| | **(1)** | | **(2)** | | **(3)** | |
| 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) | 0.01725 | | - | | 0.01707 | |
| Num_EOD_Cases_First(t) | - | | 0.00043 | | - | |
| Num_EOD_Cases_Subsequent(t) | - | | -0.00554 | *** | - | |
| Num_Infoleak_cases(t) | - | | 0.01494 | | - | |
| Liquidity(t) | 0.02309 | *** | 0.21432 | *** | -0.01838 | *** |
| Interaction_Liquidity_EOD (t) | - | | - | | 0.21350 | *** |
| IPR_index(t) | 0.21377 | *** | 0.02264 | *** | 0.02569 | *** |
| MV_Decile(t) | 0.01962 | *** | 0.01961 | *** | 0.01951 | *** |
| ROA(t) | -0.02887 | *** | -0.02875 | *** | -0.02994 | *** |
| PPETA(t) | 0.02823 | | 0.02768 | | 0.02751 | |
| LEV(t) | 0.03438 | | 0.03303 | | 0.03562 | |
| CAPEXTA(t) | -0.18833 | *** | -0.18587 | *** | -0.19065 | *** |
| Q(t) | -0.00422 | *** | -0.00417 | *** | -0.00428 | *** |
| Year and Firm fixed effects | Included | | Included | | Included | |
| Sector fixed effects | Included | | Included | | Included | |
| | | | | | | |
| Number of observations used | 97,148 | | 97,148 | | 97148 | |
| Adjusted R2 | 0.72600 | | 0.72600 | | 0.7262 | |

# Table V
# Random Effects Specification

Table 5 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 or IPR) + c2'Interaction_Country_variable_EOD + c3*Interaction_Liquidity_EOD + d'Controls + YR(t) + Industry(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. Similary, 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) EOD Dummy | | (2) Number of EOD Cases | | (3) Enforcement index | | (4) IPR Index | | (5) EOD & Liquidity | |
|---|---|---|---|---|---|---|---|---|---|---|
| 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) | -0.00313 | | | | -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) | 0.03244 | *** | 0.03230 | *** | 0.02548 | *** | 0.03014 | *** | 0.03048 | *** |
| Enforecement_index | | | | | 1.39727 | *** | | | | |
| IPR_Index | | | | | | | 0.10116 | *** | 0.10152 | *** |
| Interaction_Enforcement_EOD | | | | | 0.03676 | * | | | | |
| Interaction_IPR_EOD | | | | | | | 0.00159 | | | |
| Interaction_Liquidity_EOD | | | | | | | | | -0.00266 | ** |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| MV_Decile(t) | 0.00246 | * | 0.00242 | * | 0.00579 | *** | 0.00461 | *** | | *** |
| ROA(t) | -0.01930 | *** | -0.01929 | *** | -0.01656 | *** | -0.01923 | *** | 0.00458 | *** |
| PPETA(t) | -0.00182 | | -0.00191 | | 0.01521 | * | 0.00904 | | -0.01938 | |
| LEV(t) | 0.01526 | | 0.01498 | | 0.02433 | ** | 0.03146 | *** | 0.00890 | *** |
| CAPEXTA(t) | -0.08043 | *** | -0.07995 | *** | -0.05881 | *** | -0.07135 | *** | 0.03156 | *** |
| Q(t) | -0.00300 | *** | -0.00297 | *** | -0.00395 | *** | -0.00389 | *** | -0.07175 | *** |
| LN_Firm_Age(t) | 0.28267 | *** | 0.28291 | *** | 0.27571 | *** | 0.26254 | *** | -0.00390 | *** |
| Year fixed effects | Included | | Included | | Included | | Included | | Included | |
| Industry fixed effects | Included | | Included | | Included | | Included | | Included | |
| Number of observations used | 97,148 | | 97,148 | | 90,272 | | 97,148 | | 97,148 | |
| R2 | 0.2314 | | 0.2310 | | 0.2550 | | 0.2543 | | 0.2541 | |

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

| | (1) EOD Dummy | | (2) Number of EOD Cases | | (3) Enforcement index | | (4) IPR Index | | (5) EOD & Liquidity | |
|---|---|---|---|---|---|---|---|---|---|---|
| EOD_Dummy_First(t) | 0.00668 | | | | 0.01014 | | 0.01059 | | 0.00861 | |
| EOD_Dummy_Subsequent(t) | -0.09415 | *** | | | -0.07728 | *** | -0.08366 | *** | -0.05779 | *** |
| Infoleak_dummy(t) | 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) | 0.06359 | *** | 0.06333 | *** | 0.05979 | *** | 0.06218 | *** | 0.06357 | *** |
| Enforecement_index | | | | | 1.44248 | *** | | | | |
| IPR_Index | | | | | | | 0.16000 | *** | 0.15408 | *** |
| Interaction_Enforcement_EOD | | | | | -0.22679 | *** | | | | |
| Interaction_IPR_EOD | | | | | | | -0.03288 | *** | | |
| Interaction_Liquidity_EOD | | | | | | | | | -0.01676 | *** |
| MV_Decile(t) | 0.01654 | *** | 0.01632 | *** | 0.02055 | *** | 0.01768 | *** | 0.01881 | *** |
| ROA(t) | -0.07782 | *** | -0.07787 | *** | -0.06956 | *** | -0.06673 | *** | -0.06829 | *** |
| PPETA(t) | -0.00010 | | -0.00025 | | 0.03112 | | 0.03267 | * | 0.03136 | |
| LEV(t) | -0.04453 | * | -0.04585 | * | 0.00319 | | 0.00656 | | 0.00769 | |
| CAPEXTA(t) | -0.25371 | *** | -0.25237 | *** | -0.20404 | *** | -0.22188 | *** | -0.21957 | *** |
| Q(t) | -0.00753 | *** | -0.00746 | *** | -0.00915 | *** | -0.00811 | *** | -0.00817 | *** |
| LN_Firm_Age(t) | 0.26412 | *** | 0.26421 | *** | 0.23686 | *** | 0.22725 | *** | 0.22608 | *** |
| Year fixed effects | Included | | Included | | Included | | Included | | Included | |
| Industry fixed effects | Included | | Included | | Included | | Included | | Included | |
| Number of observations used | 97,148 | | 97,148 | | 90,272 | | 97,148 | | 97,148 | |
| R2 | 0.2309 | | 0.2305 | | 0.2750 | | 0.2687 | | 0.2534 | |

# Table VI
# Robustness checks

Table 6 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 Patent applications that are eventually granted as the dependent variable. Model (5) uses Patent applications that are eventually granted which has been adjusted for truncation bias as the dependent variable. Model (6) uses variables without any winsorization.

In Panel B: 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) Applied & granted patents | | (5) Adjusted Applied & granted patents | | (6) Without winsorization | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| EOD_Dummy_First(t) | 0.00048 | | -0.00253 | | -0.02384 | *** | -0.00086 | | -0.00449 | | 0.00048 | |
| EOD_Dummy_Subsequent(t) | -0.02105 | *** | -0.02430 | *** | -0.05051 | *** | -0.01001 | *** | -0.01460 | *** | -0.01978 | *** |
| Infoleak_dummy(t) | -0.00339 | | -0.00286 | | -0.01769 | ** | 0.01532 | *** | 0.01355 | *** | -0.00498 | |
| IPR_Index(t) | 0.11904 | *** | 0.10969 | *** | 0.09817 | *** | 0.10144 | *** | 0.10697 | *** | 0.10256 | *** |
| Liquidity(t) | 0.03236 | *** | 0.03587 | *** | 0.05556 | *** | 0.02817 | *** | 0.03133 | *** | 0.02982 | *** |
| Interaction_Liquidity_EOD(t) | -0.00336 | ** | -0.00224 | | -0.00535 | ** | 0.00037 | | 0.00039 | | -0.00200 | |
| MV_Decile(t) | 0.00060 | | 0.00451 | *** | 0.01706 | *** | 0.00514 | *** | 0.00338 | *** | 0.00281 | ** |
| ROA(t) | -0.01983 | *** | -0.02518 | *** | -0.04814 | *** | -0.02090 | *** | -0.01988 | *** | -0.00001 | |
| PPETA(t) | 0.00927 | | 0.00549 | | 0.02132 | | 0.00829 | | 0.00444 | | 0.00764 | |
| LEV(t) | 0.03307 | *** | 0.03960 | *** | -0.04294 | ** | 0.01698 | * | 0.01206 | | 0.00006 | |
| CAPEXTA(t) | -0.07043 | *** | -0.09071 | *** | -0.02307 | | -0.09796 | *** | -0.08535 | *** | -0.00060 | |
| Q(t) | -0.00354 | *** | -0.00520 | *** | -0.00610 | *** | -0.00439 | *** | -0.00424 | *** | 0.00000 | *** |
| LN_Firm_Age(t) | 0.37413 | *** | 0.25431 | *** | 0.24447 | *** | 0.17644 | *** | 0.19715 | *** | 0.28811 | *** |
| Year fixed effects | Included | | Included | | Included | | Included | | Included | | Included | |
| Industry fixed effects | Included | | Included | | Included | | Included | | Included | | Included | |
| Number of observations used | 66,195 | | 70,752 | | 26,396 | | 97,148 | | 97,148 | | 97148 | |
| R2 | 0.2935 | | 0.2610 | | 0.2788 | | 0.2357 | | 0.2378 | | 0.2474 | |

**Panel B: 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 VII
# Liquidity Deciles

Table 7 reports the Firm Random Effects regression results of the model INNOV_PAT(i,t+1) = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c1'IPR_Index +d1*Liquidity + e'Controls + YR(t) + Industry(i) + error(i,t), for the 10th, 20th, 80th and 90th deciles of the Liquidity(t) measure. Year fixed effects YR(i) and Industry(i) fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

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

# Table VIII
## Manipulation on Month End Dates

Table 8 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 from and weak form manipulation dummies. Year fixed effects and industry fixed effects 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 IX
# 2SLS Specification

Table 9 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 from First stage (i,t) \ Infoleak_Dummy from First stage (i,t) + c'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)<br>EOD manipulation** | | **(2)<br>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 X
# Propensity scoring matching analysis

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

Next, the nearest (four-nearest) 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** | |
| *Nearest neighbour estimator* | | | | | | | | |
| ATT Difference-in-difference estimator | -0.21285 | | -0.01454 | | -0.04482 | | -0.01164 | |
| Standard error | 0.05233 | | 0.00399 | | 0.09350 | | 0.00606 | |
| *t-statistics* | -4.07 | *** | -3.65 | *** | -0.48 | | -1.92 | * |
| | | | | | | | | |
| *Four-nearest neighbour estimator* | | | | | | | | |
| ATT Difference-in-difference estimator | -0.18912 | | -0.01397 | | -0.09412 | | -0.01347 | |
| Standard error | 0.05789 | | 0.00449 | | 0.09318 | | 0.00603 | |
| *t-statistics* | -3.27 | *** | -3.11 | *** | -1.01 | | -2.23 | ** |

**Panel B: Probit regression excludes Liquidity(t) as an independent variable**

Probit regression

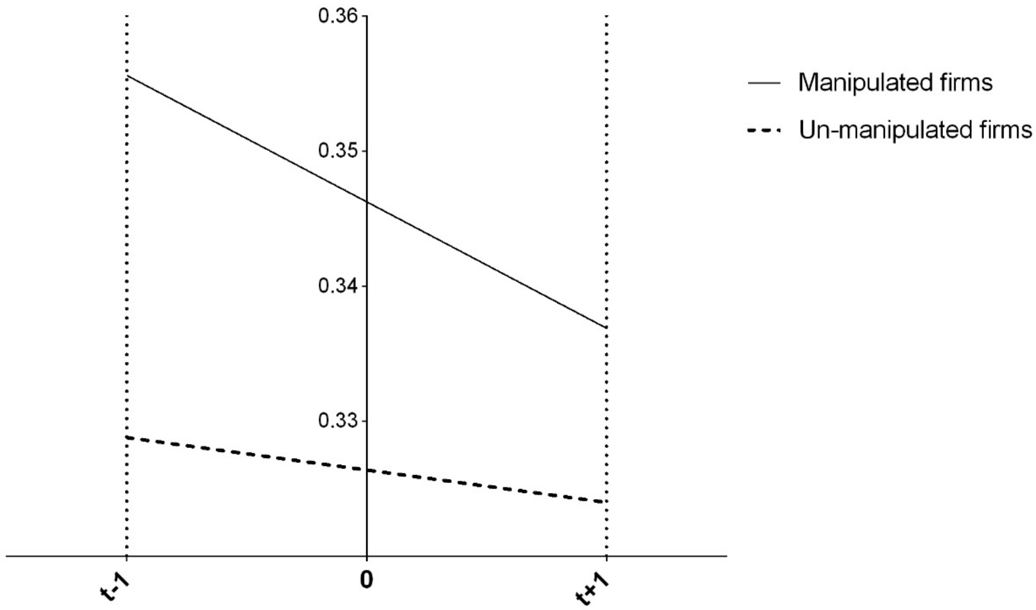
| Dependent variable | **EOD_Dummy(t)** | | **Infoleak_Dummy(t)** | |
|---|---|---|---|---|
| INNOV_PAT(t-1) | 0.00089 | | 0.04465 | *** |
| IPR_Index(t) | 0.21712 | *** | 0.12074 | *** |
| Enforcement_index(t) | -5.26973 | *** | -0.90855 | *** |
| MV_Decile(t) | 0.05612 | *** | 0.07194 | *** |
| ROA(t)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

Average Treatment Effect on the Treated (ATT)

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

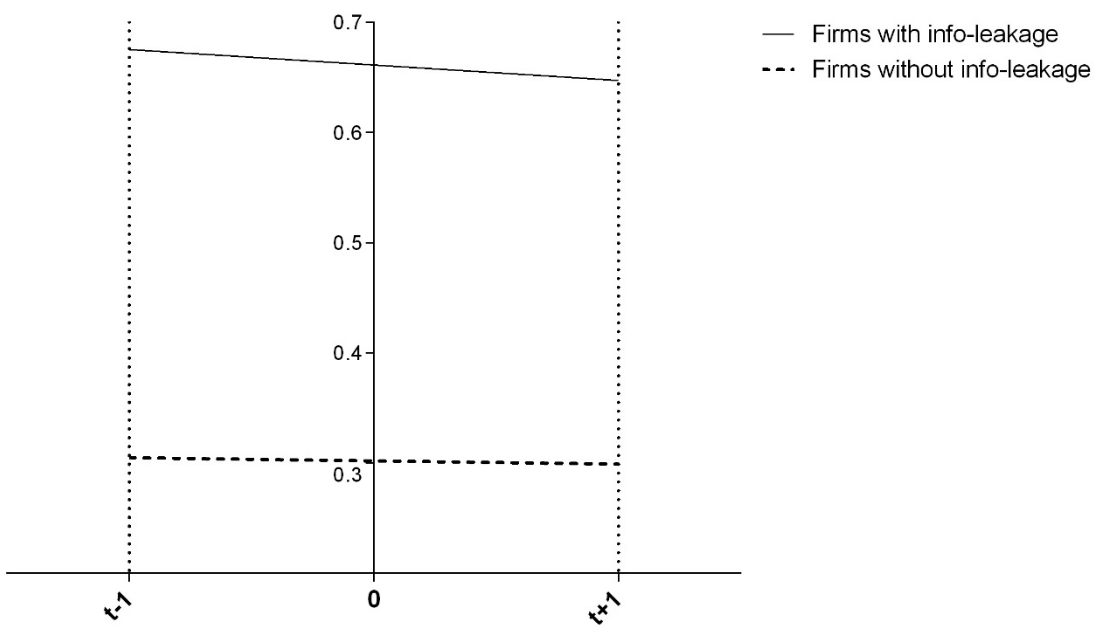
## Figure I
## Comparison of Means – End of Day Price manipulation

Figure 1 compares the means of INNOV_PAT one period before the manipulation (t-1) to the mean INNOV_PAT 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.




## Figure II
## Comparison of Means – Information leakage

Figure 2 compares the means of INNOV_PAT one period before the occurrence of information leakage (t-1) to the mean INNOV_PAT one period after the information leakage (t+1) for firms that have experienced information and for those that have not experienced any information leakage.



# 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_treatement(t) is the treatement 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 Treatement 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 treatement.

**Panel A: Probit regression**

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

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

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