Market Manipulation and Innovation

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

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

Rejo Peter
DeepR Analytics, Co-founder & CEO
20 Bay St, Floor 11, Toronto,
Ontario M3J 1P3, Canada
rejopeter@deepranalytics.com

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

This Draft: September 24, 2020

Acknowledgments: We thank the seminar participants at Capital Markets CRC, SKEMA Business School, and York University for helpful comments and suggestions. We owe thanks to the seminar participants at the Canadian Law and Economics Association, Financial Management Association, Capital Markets CRC (Macquarie University, University of New South Wales, University of Technology, Sydney, and University of Sydney), Financial Management Association, Miami University, SKEMA Business School, Steven's Institute of Technology, University of Ottawa, University of Toronto, and University of Chile, Santiago. All errors are our own. Douglas Cumming gratefully acknowledges the Social Science Research and Humanities Council of Canada for financial support. Rejo Peter gratefully acknowledges the support of Capital Markets CRC (CMCRC) and Michael Aitken for the opportunity to visit CMCRC throughout 2015 to work on this project. Monika Tarsalewska acknowledges funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 665778 and National Science Center, Poland 2016/23/P/HS4/04032 POLONEZ.

Market Manipulation and Innovation

Abstract

End-of-day stock price manipulation is generally associated with short-termism, long-term damage to equity values, and reduced incentives for employees to innovate. We use a sample of suspected stock price manipulation events based on intraday data for stocks from nine countries over eight years and find evidence of negative effects of market manipulation on innovation. We show that these negative effects are particularly harmful to innovation in markets with low intellectual property rights and high shareholder protection.

Keywords: Market Manipulation, End-of-Day Dislocation, Patents, Innovation, Intellectual Property Rights, Shareholder Protection

JEL Classification: G14; G18; O30

The stock-price manipulation [has] consequences…net disinvestment, loss of shareholder value, ***diminished investment in innovation***, destruction of jobs, exploitation of workers, *windfall gains for activist insiders*, rapidly increasing inequality and sustained economic stagnation.

–Forbes[1]

1. Introduction

Financial market misconduct comes in many forms. Two of the most commonly observed (and, therefore, most 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; Bernile et al., 2015; Aitken et al., 2015b) and end-of-day manipulation (Atanasov et al., 2015; Aitken et al., 2015a; Lin et al., 2019). When there is information only known to insiders, this information may be used to disadvantage the counterparties in the trade and, ultimately, damage long-term firm value. Research has shown that restricting insider trading has a positive impact on innovation (Levine et al., 2017).

However, it is less well known that there are massive incentives to manipulate closing stock prices by ramping up end-of-day trading and pushing closing prices to artificially high levels. End-of-day (EOD) prices are used to determine the expiration value of derivative instruments and directors' options, estimate the price of seasoned equity issues, evaluate broker performance, compute the net asset values of mutual funds, and to compute stock indices (Aitken et al., 2015a).[2]

In this paper, we explore, for the first time, a possible link between market manipulation and innovation. The link between a microstructure event and a real corporate outcome is rare, as these two literatures scantly talk to one another.[3] Theory suggests, however, two primary perspectives linking market manipulation to innovation: an *incentives channel* and a *financing channel*. Regarding the *incentives channel*, the presence of market manipulation is associated with short-termism of a firm's orientation, which is inconsistent with a long-term managerial focus on innovation. Over- or undervaluation of firm equity can cause agency problems (Marciukaityte and

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

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

[3] One prior paper shows the relationship between stock liquidity and innovation (Fang et al., 2014).

Varma, 2008), which, in turn, may impede innovation. Market manipulation may also damage a firm's equity values and reduce incentives for employees to innovate. Ferreira et al. (2014) find that public firms have fewer incentives when exploring radical new innovations, because the rapid incorporation of good news into market prices creates incentives for short-termist behavior. Bereskin et al. (2018) find that firms engaging in managerial manipulation of R&D expenditures have reduced levels of firm innovation. Market manipulation may be yet another reason why public firms innovate less and more frequently engage in short-termism. Regarding the *financing channel*, market manipulation damages the ability of firms to go back to the market to raise capital for financing long-term projects (Amiram et al., 2018).

In this paper, we empirically study the link between market manipulation and innovation for the 2003-2010 period by assembling a sample of 97,148 firm-year observations across nine countries (Australia, Canada, China, India, Japan, New Zealand, Singapore, Sweden, and the United States). Market manipulation can be difficult to prove, because trading ahead of information announcements may simply be attributable to market anticipation, unusual volatility, or EOD market activity. Even in the case of prosecution, there may be limited or publicly unavailable data.

Our measure of market manipulation overcomes these problems by using suspected cases of dislocation of "closing"' or EOD firm prices. This measure of EOD stock price manipulation is used by surveillance authorities around the world through SMARTS, Inc. An EOD stock price movement is defined as dislocated if it has been 4 standard deviations away from its mean price change during the past 100-trading day benchmarking period at the end of the trading day, and if stock price then reverts back to the mean price the subsequent morning (see the Appendix for more details). Thus, our data are based directly on surveillance data of suspected EOD stock price dislocations derived from alerts (computer algorithms that send messages to surveillance authorities). The advantages of these measures are that they avoid delays in enforcement, and they are uniform, without any bias from enforcement differences across firms or countries over time. We note that suspicion of firm problems can be equally as harmful as actual litigation and can impact management's focus on short-termism and damage equity values and divert attention away from innovative activities.

We merge our dataset of suspected EOD stock price manipulations with measures of innovative activity obtained from PATSTAT, the European Patent Office's Worldwide Patent Statistical Database. We define the three major measures of innovation as: 1) the number of patents, 2) the number of citations, and 3) the ratio of citations per patent. These measures allow us to capture the quantity, quality, and importance of a firm's innovative activity.

To assess the results, we use a number of econometric techniques. First, we run OLS regressions with time and firm fixed effects and clustered errors. We also run regressions on matched samples based on propensity scores and entropy balance. We find that EOD stock price dislocations decrease innovative activity. We argue that this is consistent with the notion that manipulation is associated with a firm's short-term orientation, long-term harm to its equity values, and reduced incentives for employees to innovate. The economic significance of this effect is greater when the dislocation is more likely to be attributable to manipulation, such as at the end of the month, quarter, and/or year. The data indicate that EOD stock price dislocation has a pronounced negative impact on patenting, even after controlling for other market efficiency variables such as liquidity.

Our analysis also explores the importance of country-level factors that affect innovation, such as intellectual property rights and shareholder protection rights across countries. We find that the negative link between EOD stock price manipulation and innovation is only significant in countries with lower levels of intellectual property rights. This suggests that EOD manipulation can damage equity values more severely if intellectual value is not protected, because firms cannot overcome the information asymmetry and cannot clearly communicate the value of their projects. We also find that the link is significant only in countries with higher levels of shareholder protection. We posit that, in an environment where minority shareholders are overly protected, they may take opportunistic actions against undiversified stockholders (Belloc, 2013). Thus, EOD manipulation can damage equity values more severely because it can lead to misvaluing firm equity.

Our findings are robust to numerous checks, such as including/excluding the U.S. during financial crisis years, considering patent applications versus patent grants, controlling for liquidity, matching techniques, and other factors.

The link between market manipulation and patenting is tied to literature on, e.g., market microstructure, financial misconduct and regulation, and innovation. One paper in particular, Levine et al. (2017), is the most closely related to ours. The authors use a sample of 74 countries from the 1976-2006 period, and explore whether insider trading enforcement laws affect subsequent innovation at the country level. They find a strong positive link.

Similarly to Levine et al. (2017), we find that firms would benefit by restricting EOD stock price manipulation. However, our analyses are distinct from theirs in several key ways. We examine whether there were actual events of apparent manipulation based on alerts (computer algorithms) that investigate historical microstructure data and we focus on specific EOD stock price manipulation.

Our evidence offers a number of important policy implications. Manipulation is common, and countries spend significant amounts of money to detect securities fraud (Jackson and Roe, 2009). Our evidence suggests there are significant externalities to manipulation, including a reduction in innovation. In view of these externalities, we find that expenditures on the enforcement of securities regulations around the world may be more important than previously thought, as they have a strong impact on real investment.

The remainder of this paper is organized as follows. Section 2 discusses the economic links between market manipulation and innovation and develops our hypothesis. Section 3 presents the data and explains our variables, while Section 4 describes our research design. The empirical results and robustness tests are presented in Section 5. Section 6 offers our conclusions.

2. Hypotheses Development

2.1. Economic Link between Market Manipulation and Innovation

Financial market misconduct is viewed as extremely costly to financial markets, and it is thus an active area of scholarly study (Kyle and Viswanathan, 2008). We classify research on the consequences of financial market misconduct into four categories: 1) managerial consequences, such as salaries, termination, and jail terms (Karpoff et al., 2008a; Bereskin et al., 2014; Aharony et al., 2015); 2) country-level stock market participation (La Porta at el., 2006; La Porta et al., 1997, 1998, 2002; Cumming et al., 2011) and individual stock market participation (Giannetti and Wang, 2016); 3) consequences for funds under management, such as hedge funds (Bollen and Pool, 2009; Cumming and Dai, 2010; Gerken and Dimmock, 2012, 2016), mutual funds (Chapman et al., 2014), and venture capital funds (Cumming and Walz, 2010; Johan and Zhang, 2020); and 4) share price declines and legal penalties (Karpoff et al., 2008b; Karpoff and Lou, 2010; Vismara et al., 2015). We extend this stream of research by examining a fifth, previously unexplored, category: the effect of financial market misconduct on real investment decisions, such as innovation. Innovation is essential to a firm's success, because it allows a firm to keep its competitive advantage.

We posit several possible ways that EOD stock price manipulation may affect innovation. First, the EOD stock price manipulation might affect innovation through the *financing channel*. Innovation typically involves high-risk projects with uncertain future outcomes. They require significant resources committed to long-term investments, and it can be difficult for investors to value those high-risk projects precisely (Hall, 2002). Firms can finance new investments by either raising equity or debt. Myers and Majluf (1984) show in a theoretical model, where managers know more about the project than investors, that it is difficult to sell securities at a fair price. When communicating the potential payoffs to investors is subject to information asymmetry problems, it can increase the cost of capital (Hall and Lerner, 2010). Therefore, firms may actually forgo positive Net Present Value (NPV) projects due to information asymmetry (Mayers and Majluf, 1984). Reducing information asymmetry is challenging in the case of innovative projects, because they do not have collateral, and the technical details are generally confidential and cannot be publicly released. Therefore, communicating the value of the project to investors in such an environment is difficult.

The theory of market manipulation suggests that price-destabilizing speculation by traders can affect stock prices (Jarrow, 1992). Stock market manipulation typically harms a firm and other investors. It can weaken the firm by making it a less desirable investment to outside investors and, hence, making it harder for the firm to raise capital in the future (Cumming et al., 2020). There is evidence that market manipulation and fraud can significantly affect firms' long-term economic outcomes (Karpoff et al., 2008a, 2008b; Karpoff et al., 2012). Stock price manipulations typically reduce long-term equity values and trust in the market (Aggarwal and Wu, 2006; Karpoff et al., 2008a, 2008b; Agrawal and Cooper, 2015; Aitken et al., 2015a, 2015b). As a result, managers may anticipate equity misvaluation by investors. They may forgo harder-to-value projects and invest in safer, less innovative projects. Therefore, EOD price dislocation will impact (non-transparent) projects with a high degree of information asymmetry, like innovation, rather than (transparent) projects with less information asymmetry.[4] We thus predict that EOD stock price manipulation

[4]It is important to note that the marginal impact of additional information asymmetry from EOD stock price manipulation might be small for firms with radical innovation (i.e., highly non-transparent) in the first place. Yet, such firms would face high external financing costs and would rather spin off those projects rather than rely on funding from public markets and keeping the projects in-house.

will have a negative impact on innovation. This effect will be more pronounced if firms are subject to subsequent manipulation, in contrast to one-time manipulation.

Second, EOD stock price manipulation may affect innovation through the *incentives channel*. CEOs and innovators are frequently compensated with equity and options in order to align the interest of the manager and shareholders. Manso (2011) and Ederer and Manso (2013) suggest that, in order to promote innovation, firms must withstand early failures and reward long-term success. Therefore, it is important that stock prices reflect this long-term nature of innovation.

EOD prices are particularly important, because they determine how options compensation is tied to equity prices (Aitken, et al., 2015a). Because EOD manipulation is likely to affect firm insiders on days when options expire, it may distort the equity incentives by adding additional noise to the equity compensation, and hence making it less effective. Furthermore, reduced long-term prospects for a firm worsen its ability to raise future equity (Brown et al., 2009; Brown et al., 2013), while shifting managerial focus to short-termism and short-term pay structures (Peng and Röell, 2014). Thus, managers may be more likely to reduce long-term investments in innovation, focusing instead on improving equity values in the short-term. This behavior is likely to hinder successful innovation, which generally requires a long-term horizon (Manso, 2011) and incentive pay (Shen and Zhang, 2017). Therefore, we posit that EOD stock price manipulation will have a negative impact on innovation.[5]

In general, both predictions, for the *financing channel* and the *incentives channel*, suggest a negative effect of EOD stock price manipulation on innovation. As we note earlier, we also posit this effect will be stronger for subsequent rather than one-time manipulation. We test those conjectures in subsequent sections.

2.2. The Role of Intellectual Property Rights

The protection of property rights varies at the international level and has potential implications for firm innovative activity (Johnson, et al., 2002; Levine, 2005). Innovation typically requires a significant long-term commitment and investment, with a high probability of failure (Hall, 2002; Manso, 2011; Ederer and Manso, 2013). In order to obtain debt or equity financing for such investments, firms need to reduce information asymmetry and communicate the potential

[5] Note that it does not matter whether insiders or outsiders are responsible for the EOD manipulation.

payoffs to investors (Leland and Pyle, 1977; Himmelberg and Petersen, 1994; Hall, 2002; Hall and Lerner, 2010). Intellectual property rights (IPR) protection plays a crucial role here, as firms are more likely to disclose detailed information about their inventions in environments where intellectual property rights are protected, so they can lower information asymmetry. Thus, the adverse effects of EOD stock price manipulation should have a smaller effect on raising equity in countries with high levels of intellectual property rights protection, because firms can communicate about their inventions and disclose technical details without concerns that such disclosures will benefit their competition. However, in environments with low intellectual property protection, firms are less likely to disclose invention details, and informational asymmetry may be more difficult to overcome. Accordingly, the adverse effects of EOD stock price manipulation should be more pronounced, as they increase the costs of information asymmetry. We therefore predict that the negative association between EOD stock price manipulation and innovation would be more pronounced in countries with lower levels of intellectual property rights protection.

2.3. The Role of Shareholder Protection Rights

The laws protecting minority shareholders can affect the link between EOD stock price manipulation and innovation. In general, minority shareholders can be at risk of expropriation if managers pursue the goals of majority shareholders. Therefore, in environments with high shareholder protection rights (SPR), the discretion of majority shareholders may be limited, and the means of control may be transferred to minority shareholders (La Porta et al., 1998; Rajan and Zingales, 1998).

On one hand, one might expect that the cost of information asymmetry would be greater in countries with poor shareholder protection rights (La Porta et al., 1998, 2002). We would predict, then, that the negative association between EOD stock price manipulation and innovation would be more pronounced in countries with weak shareholder protection rights. Put differently, legal standards for protecting minority investors should mitigate the harm of manipulation on firm outcomes resulting from market manipulation.

On the other hand, other factors could lead us to an opposite and somewhat counterintuitive prediction. Investing in long-term projects is often linked to the presence of a specific type of institutional investor, who is focused, long-term, and dedicated (Bushee, 1998, 2001). Investors who are diversified, short-term, and more transient tend to discourage innovation (Bushee, 1998, 2001; Aghion et al., 2005; Borochin and Yang, 2017; Borochin et al., 2019). Therefore, given that the economic goals of shareholders differ, the conflict of interests might cause small and diversified shareholders to take opportunistic actions against undiversified stockholders (Belloc, 2013). In stronger minority shareholder protection environments, where the rights of minority shareholders with short-term interests are relatively stronger than those of long-term dedicated investors, EOD stock price manipulation may be particularly severe, as it would further attenuate the ability to raise equity. We therefore predict that the negative association between EOD stock price manipulation and innovation would be more pronounced in countries with strong shareholder protection rights.

3. Data and Variable Construction

3.1. Sample Selection and Data Sources

This study uses data from eleven stock exchanges from nine countries over the 2003-2010 period. The countries include: Australia (the Australian Securities Exchange [ASX]), Canada (the TSX Venture Exchange [TSXV]),[6] China (the Shanghai Stock Exchange [SSE]), India (the Bombay Stock Exchange [BSE] and the National Stock Exchange of India Ltd. [NSE]), Japan (the Tokyo Stock Exchange [TSE]), New Zealand (the New Zealand Stock Exchange [NZX]), Singapore (the Singapore Exchange Ltd. [SGX]), Sweden (the Stockholm Stock Exchange [STO]), and the U.S. (the Nasdaq Stock Market [NASDAQ] and the New York Stock Exchange [NYSE]). We limited the number of exchanges due to data availability of EOD stock price manipulation from the Capital Markets Cooperative Research Centre (CMCRC).

Patent data comes from PATSTAT, which includes 90 million patent documents from over 100 patent offices around the world. The PATSTAT database is published biannually; we use the Autumn Edition 2014 here. It provides information on first publication and grant dates, citation links, technological classifications, and applicant and inventor identifications for each patent application. We augment this data with the ECOOM-EUROSTAT-EPO PATSTAT Person Augmented Table (EEE-PPAT), which provides sector codes and harmonized company names for each application (du Plessis et al., 2009; Magerman et al., 2009; Peeters et al., 2009). Manipulation

[6] Our results remain the same if we exclude the TSXV market.

data is obtained from SMARTS Group Inc. and the CMCRC. SMARTS Group Inc. provides market surveillance products to over forty stock exchanges around the world. We obtain firm-level data from Datastream.

3.2. Measuring Innovation

In this study, we use three different measures of firms' innovative activity: 1) the number of patent applications made by a firm in a year, 2) the number of citations received by the patents, and 3) the number of citations per patent. The number of patent applications proxies for the quantity or productivity of innovation; the number of citations received and citations per patent capture the relative quality and importance of innovation.

We use the logarithm of 1 plus the number of patent applications in the year t+1, *INNOV_PAT*, as our main dependent variable. We use the logarithm of the number of patents, because the patent data are right-skewed, with the 75^{th} percentile equal to 0. We add 1 to the number of patents before taking the logarithm to ensure we do not have any missing values for firms with zero patents. Finally, we use the application date instead of the grant date, because the application date is closer to the actual date of innovation.

The second variable, *INNOV_CITE*, is the natural logarithm of 1 plus the number of citations received for patents filed in t+1. Following Hall et al.'s (2001, 2005) methodology, we adjust this measure for the truncation bias using the following procedures.

First, for each cohort of patents applied for between 1991 and 2002, we obtain the citation lags by using twelve years' of actual citation data. For example, for patents applied for in 1991 (Cohort 1), we measure the number of citations received in each year from 1991 (citation lag of 0) to 2002 (citation lag of 11). Similarly, for patents applied for in 2002 (Cohort 12), we measure the number of citations received in each year from 2002 (citation lag of 0) to 2013 (citation lag of 11).

Next, for each major IPC (International Patent Classification) technology classification of patents, k, in each cohort, we obtain the citation lag distribution, W. W equals the proportion of citations received with lags of 0 to 11 years with the total number of citations received. Subsequently, we compute the cumulative share of citations received with lags of 0 to 11 within each technology classification of patents. We average the cumulative share of citations across the twelve cohorts.

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.

The third measure of innovation is its intensity, *INNOV_CITE/ PAT*, the natural logarithm of 1 plus the number of citations received for patents filed in the year t+1, divided by the number of patents filed in the year t+1.

As part of our robustness checks, we also use an alternative measure for the number of patents applied for and eventually granted, adjusted again for the truncation bias (*INNOV_PAT_GRNT_ADJ*). Using only patent applications that were eventually granted can introduce a truncation bias, because of the lag between the patent application and the grant date. We correct for this bias by using Hall et al.'s (2001, 2005) methodology. We compute the grant lag distribution for patents filed and granted between 1991 and 2002. The truncation-adjusted patents are then computed as follows:

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

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.

Note that using patents as a measure of innovation, however, has some disadvantages. For example, it does not take into account inter-industry differences in intensity and duration of patents. To rectify this, we include firm-level controls for patent data. Using the number of patent applications also does not capture how efficiently firms convert their innovative inputs (R&D expenditures and intangible inputs) into innovative outputs. We therefore include R&D expenditures as one of our controls.

3.3. Market Manipulation

As a measure of manipulation, we use EOD stock price dislocation alerts computed by the CMCRC and SMARTS. An EOD price alert is created by looking at the price change between the last trade price (P_t) and the last available trade price 15 minutes before the continuous trading period ends (P_{t-15}). For securities exchanges with a closing auction, we use the close price at auction ($P_{auction}$). We consider a price movement as dislocated if it is 4 standard deviations away from the mean price change during the benchmark period for the past 100 trading days. To be considered a case of EOD price dislocation, at least 50% of the price dislocation must revert at the open on the next trading day. Hence, the price movements between the last trade price (P_t) and the next day's opening price (P_{t+1}), and between the last trade price (P_t) and the last available trade price 15 minutes before the continuous trading period ends (P_{t-15}), must be greater than 50%:

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

EOD manipulation events are measured in the year prior to the innovation year. They pertain to manipulations not caused by the announcement of the innovation outcome but, instead, in reference to other firm events.

3.4. Control Variables

We follow previous literature on innovation such as Fang et al. (2014) and Blanco and Wehrheim (2017) in order to decide on a set of control variables that affect innovation. Fang et al. (2014) show that firm liquidity is correlated with innovation. We, therefore, include LIQUIDITY, which is computed as the natural logarithm of the inverse of the AMIHUD measure of illiquidity. We compute the AMIHUD as follows:

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

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

We control for firm size by using MV, the market value decile variable, which takes a value of 1 to 10 based on which market value decile firm i belongs to within each country-year grouping at the end of year t. We control for firm profitability by using return on assets, ROA, which is measured as income before extraordinary items divided by the book value of total assets;

investment in innovation, RDTA, which is measured as research and development expenditures divided by the book value of total assets measured at the end of fiscal year t, and set to 0 if missing; asset tangibility, PPETA, which is measured as property, plant, and equipment expenditures divided by the book value of total assets; leverage, LEV, which is measured as the book value of debt divided by the book value of total assets; investment in fixed assets, CAPEXTA, which is measured as capital expenditures scaled by the book value of total assets; and TOBIN Q, which is firm i's market-to-book ratio during fiscal year t, calculated as the market value of equity, plus the book value of debt, divided by the book value of assets. Additionally, we also introduce a variable MKTVOL that proxies for stock return volatility. We calculate it as follows. We begin with the daily high/low index value of the most representative market index from each trading venue as these indices are already market cap weighted (by their constituents). Then we calculate the daily log high-low return for each index and assign them into annual distribution. Next we take the standard deviation of each annual distribution for every index and taking the log of these deviations creates the variable for each index-year pair. We provide detailed variable definitions in Table A1 in the Appendix.

Consistent with the large intellectual property rights literature documenting its critical role in spurring innovation (e.g., Branstetter et al., 2006; Blind, 2012), we also include IPR_INDEX as one of our controls. The IPR index changes over time, so it is not impacted by firm fixed effects. Finally, following previous studies, we winsorize all variables at the 1% and 99% levels.

3.4. Sample Distribution and Descriptive Statistics

Table 1 provides sample distributions by year in Panel A and by country in Panel B. The sample is fairly well balanced over time. The average frequency of EOD stock price manipulation (EOD_DUMMY) varies from 20% in 2010 to 26% in 2004, which suggests that one in five firms experienced EOD stock price manipulation at least once over a particular year. This is comparable to the findings of Aitken et al. (2015a), who show there were 36.56 suspected cases of EOD stock price manipulation among 2,196 observations, or around 16%.

The country distribution shows that the sample is dominated by the U.S., followed by Japan and India. The variation in frequency of suspected EOD stock price manipulation cases varies by country, with the highest (56%) reported for India and the lowest (1%) reported for Canada.

[Table 1 here]

In Table 2, we present the descriptive statistics of the main variables used here. In general, the summary statistics are comparable to those from similar studies based on large numbers of observations, such as Fang et al. (2014). The measures of innovative activity are highly skewed, with a mean of 0.418 (0.480) and a standard deviation of 1.074 (1.507) for INNOV_PAT (INNOV_CITE). The mean for EOD_DUMMY reflects our previous discussion, with a 0.222 average and a 0.415 standard deviation. The EOD manipulations can be upwards, downwards, or both.[7] We also distinguish between first and subsequent EOD stock price manipulations. EOD_DUMMY_FIRST has an average of 0.079 and EOD_DUMMY_SUBSEQUENT of 0.143. It is 55% more likely that a firm has subsequent EOD stock price manipulations after experiencing the first one. The remaining controls are all relatively comparable, given that we are using an international sample. For example, similarly to Fang et al. (2014), who only uses U.S. firms, our firms are also quite large, with an average market value of 6.648, average ratio of R&D to total assets of 0.030, and leverage of 0.216.

[Table 2 here]

Figure 1 shows the suspected EOD stock price manipulation and percentage changes in subsequent year patent applications by industry sector (i.e. between t-1 and t+1). Note that in eight of eleven sectors (excluding oil and gas, banks, and software and computer services), the level of innovation was higher for firms that did not have suspected EOD stock price manipulation. These differences are statistically significant at the 10% level for technology hardware and equipment, mining, industrial engineering, pharmaceuticals and biotechnology (consistent with research linking capital markets to market intelligence, such as Markovitch et al., 2005), and software and computer services, and insignificant for the other industries. Overall, the evidence in Figure 1 supports our hypothesis. For the whole sample we find that the change in the number of patents between t-1 and t+1 was 0.03 when firms experienced EOD stock price manipulation, and 1.45

[7] We have 13,591 downwards and 16,091 upwards EOD stock price manipulations in our sample.

when firms did not experience EOD stock price manipulation. This difference is statistically significant at the 5% level.

[Figure 1 here]

4. Research Design

Our main model estimates the relationship between future measures of innovative activity and suspected EOD stock price manipulation. We estimate, using Ordinary Least Squares (OLS), the following model:

$$Y_{i,t+1} = \alpha + \beta EOD_{i,t} + \gamma Controls_{i,t} + \delta_t + \tau_i + \varepsilon_{i,t} \quad (1)$$

where i indicates firms and t time. The dependent variable, $Y_{i,t+1}$, represents one of the three innovative activity measures at time t+1 (e.g., INNOV_PAT, INNOV_CITE, or INNOV_CITE/PAT). The suspected EOD stock price manipulation is measured for firm i over its fiscal year t as an indicator variable (EOD_DUMMY) and as the number of suspected cases (EOD_COUNT). We also identify whether suspected EOD stock price manipulation was a first-time (EOD_DUMMY_FIRST) or subsequent (EOD_DUMMY_SUBSEQUENT) occurrence. We include a set of controls and fixed effects. δ_t are the time fixed effects, which control for variations over time, and τ_i are the firm fixed effects, which account for unobserved time-constant firm heterogeneity. We account for the possibility that the innovation measures are correlated, and we cluster standard errors by firm.

An inherent problem in this type of study is endogeneity. While unlikely, it is possible that the suspected EOD stock price manipulation may have occurred in anticipation of innovation on the basis of some unobserved characteristics. Our research design addresses this issue by creating matched samples. We match firms that experienced EOD manipulation with those that did not, based on their characteristics, and then estimate the average effect of suspected EOD stock price manipulation on innovation. We use two matching techniques. In our main analysis we use the entropy balancing technique (EBT), which is a quasi-matching approach. The advantage of EBT is that it reweights each control observation (Hainmueller, 2012). Therefore, we do not lose many observations, and the post-weighting properties of the matched treatment and control samples are virtually identical. This ensures a solid covariate balance.

5. Empirical Results

5.1. Base Model Specifications

In Tables 3 to 5, we present the OLS regression estimates of Eq. (1). Column (1) shows the results where the suspected EOD manipulation is measured as a dummy variable (EOD_DUMMY), Column (2) as a count (EOD_COUNT), and, in Column (3), where suspected EOD stock price manipulations are split into first-time (EOD_DUMMY_FIRST) and subsequent (EOD_DUMMY_SUBSEQUENT). Table 3 presents the effect of suspected EOD stock price manipulation on innovation quantity as measured by the number of patents applied for (INNOV_PAT). The estimated coefficients on EOD_DUMMY and EOD_COUNT are negative and statistically significant at the 5% and 1% levels. When we split the suspected EOD manipulations into first-time and subsequent, only EOD_DUMMY_SUBSEQUENT is negative and statistically significant at the 1% level.

The economic significance is that firms that experienced EOD manipulation have an 0.8% lower number of patents overall, and a 1.9% lower number if it is a subsequent manipulation. This equates to a decrease of 1 to 2 in the mean number of patents for an innovating firm.

We check whether our results may be driven by the fact that we use the number of patent applications as a measure of innovation quantity. In Table A2 in the Appendix, we present the results for using the number of patents filed and eventually granted in t+1, which has been adjusted for the truncation bias by using the grant lag distribution (INNOV_PAT_GRNT_ADJ). These results also indicate the negative and statistically significant effect of EOD stock price manipulation on innovation quantity and are relatively similar in magnitude to those reported in Table 3.

[Table 3 here]

In Table 4, we present the effect of suspected stock price manipulation on innovation quality as measured by the number of citations (INNOV_CITE). Similarly, the estimated coefficients are negative and statistically significant at the 1% level. Moreover, the split of suspected EOD stock price manipulations into first-time and subsequent indicates that only EOD_DUMMY_SUBSEQUENT is negative and statistically significant at the 1% level. Firms that experienced EOD manipulation have 3.31% fewer citations in general, and the number jumps to 7.49% if it is a subsequent manipulation. Thus, 3.31% and 7.49% equate to decreases in citations for an innovating firm of 6 and 14, subsequently.

[Table 4 here]

In Table 5, we present the effect of suspected stock price manipulation on innovation importance as measured by the number of citations per patent (INNOV_CITE/ PAT). These results also show a negative and statistically 1% significant decrease in citations per patent, suggesting that the importance of innovation has declined.

[Table 5 here]

We also analyze change in innovation from the year of stock manipulation to the subsequent year. The results are in Table A3 in the Appendix. We define the dependent variable INNOV_PAT_CHANGE as the difference between the total number of patents filed in t+1 and t-1, scaled by the total number of patents filed in t-1. We continue to find a negative and statistically significant effect of EOD stock price manipulation on innovation change.

As expected, several other control variables in Tables 3 and 5 are significant. For example, a 1-standard deviation increase in liquidity is associated with a 0.97% increase in the number of patents and a 1.51% increase in the number of citations in the subsequent period (Tables 3 and 4). Most notably, a 1-standard deviation increase in the IPR index is associated with an 8.03% increase in the number of patents (Table 3, Column (1)) and an 18.49% increase in the number of citations in the subsequent period (Table 4, Column (1)). These results are consistent with the large amount of literature documenting the importance of IPR in spurring innovation (e.g., Branstetter et al., 2006; Blind, 2012).

Some firm-specific control variables are statistically significant as well. The data indicate that a 1-standard deviation increase in ROA is associated with a 0.73% decrease in the number of patents in the subsequent period (Table 3, Column (1)). A 1-standard deviation increase in leverage is associated with a 2.77% increase in the number of patents in the subsequent period (Table 3, Column (1)), but this effect is insignificant in Table 3. A 1-standard deviation increase in capital expenditures over assets is associated with a 3.94% decrease in the number of patents in the subsequent period (Table 3, Column (1)). Finally, a 1-standard deviation increase in the market/book is associated with a 0.22% decrease in the number of patents in the subsequent period (Table 3, Column (1)).

5.2. Robustness Checks: Entropy Balancing

In this subsection, we present the results of the OLS regression estimated for matched samples. Although we use firm fixed effects in our OLS regressions, it is still possible that there are some omitted variables that might be correlated with EOD stock price manipulation and innovation. It is also possible that the relationship between EOD stock price manipulation and innovation is driven by unobserved characteristics affecting EOD manipulation in anticipation of innovation. We mitigate these concerns by using matched samples tests. In particular, we compare the firms with EOD stock price manipulations (treatment firms) with a control sample of firms that are similar across all of our covariates other than EOD stock price manipulation. We provide a variety of matching techniques and other checks to examine the change in patents from the pre- to post-manipulation period in order to establish a causal connection between manipulation and innovation.

The results are in Table 6. We match using entropy balancing on all dependent variables, firm age (LNAGE), pre-innovation levels (L1INNOV_PAT), year, country, and industry. In Panel A, we present the covariate balance when we match the samples using entropy. When we match using entropy balance, there is no difference in means or variances between the treatment and control firms. In Panels B, C, and D we present the coefficients of estimating Eq. (1) using an OLS model for entropy matched samples, where the suspected EOD manipulation is measured as a dummy variable (EOD_DUMMY), as a count (EOD_COUNT), and where suspected EOD stock price manipulations are split into first-time (EOD_DUMMY_FIRST) and subsequent

(EOD_DUMMY_SUBSEQUENT), respectively. We continue to find negative and statistically significant effects of EOD stock price manipulation on the three measures of innovative activity.[8]

[Table 6 here]

5.3. End-of-Month EOD Stock Price Manipulation

EOD stock price manipulations are more likely to occur at the end of the month, when manipulators have greater incentives to push up prices for reasons of compensation and option expiration. Month-end manipulation has been shown to be more common than other days of the month (Aitken et al., 2015a; Chau et al., 2019). This is a result of two factors. First, option expiry dates are typically on the last of days of the month in certain countries. Second, many traders who have purchased options and need to deliver the value of options clear their positions on the option expiry dates. We, therefore, can observe a lot of displacement. Danger et al. (2019) and Comerton-Forde and Putniņš (2007) find evidence to support this. Secondly, according to Comerton-Forde and Putniņš (2014), a significant portion of manipulation occurs on month/quarter end days, and this manipulation can be attributable to manipulation by fund managers. We, therefore, construct a variable that represents manipulation that occurred during those days; i.e., the last three days of the month (EOD_DUMMY_END). We expect the suspected cases of manipulation that occur during the last days of the month to have a more pronounced impact on innovation.

The results are in Table 7. In Panel A, we present the effects of EOD stock price manipulation that occurred during the last three days of the month on innovation, excluding firms where the EOD stock price manipulation occurred in days other than the last three days of the month on innovation. The effect of EOD manipulation is negative and statistically significant in

[8] As a robustness analysis, we use propensity score matching (PSM), where the suspected EOD manipulation probability is conditioned on firm observables (Rosenbaum and Rubin, 1983, 1984). We also matched using propensity score matching (PSM) where the suspected EOD manipulation probability is conditioned on firm observables (Rosenbaum and Rubin, 1983, 1984). In order to create the matched sample here, we estimate a probit regression of EOD manipulation on a set of observable characteristics and fixed effects. We then use the predicted propensity scores to match the firms, using the nearest-neighbor matching without replacement technique. PSM is subject to some criticism that it does not balance firm characteristics. PSM matches only on the propensity score and does not directly aim to balance on firm characteristics; the treated and control samples differ in liquidity, fixed capital, size, capital expenditures, Tobin's q, and the IPR index. Our untabulated results continue to show negative and statistically significant effects of EOD stock price manipulation on the three measures of innovative activity.

all columns. The estimated coefficients in Panel A are almost twice that of the coefficients estimated earlier.

In Panel B, we present results where we include two types of EOD stock price manipulation and interaction effect with EOD_DUMMY_END. The interaction term has a negative and statistically significant effect on innovation. This is consistent with our conjecture that the manipulations that occur during the last three days of the month have a stronger effect on innovation.

[Table 7 here]

5.4. EOD Stock Price Manipulation and Stock Liquidity

The literature argues that when stock liquidity is high, it increases the potential for a takeover threat (Kyle and Vila, 1991). This is because when stock is liquid, traders can mask their intentions in an attempt to buy firms. Managers have less control over shareholders when takeover threats increase, which might lead to managerial myopia (Shleifer and Summers, 1988). Therefore, they might sacrifice the long-term investment in innovation in order to boost short-term profits and do not allow for stock undervaluation (Stein, 1988). Furthermore, these short-term pressures can be further exacerbated by investment strategies that rely on low trading cots. High liquidity would encourage entry and exit of investors with the goal of short-term profits and further strengthen managerial myopia.

EOD stock price manipulations play a key role in takeover transactions. They are used to set deal prices, determine how options compensation is tied to equity prices, and set the compensation of the major insiders of the merging firms (Cumming et al., 2020). They are also important in various trades (Aitken et al., 2015a). We might expect that if stock liquidity is high, there are stronger incentives to manipulate the stock, as the importance of short-term pressures will arise. Thus, the effect of EOD stock price manipulation on innovation would be more pronounced when the stock liquidity is high. In order to test those predictions, we split the sample into liquidity deciles. We expect the effects to be particularly severe in the top liquidity decile and to affect innovation to a lesser extent in the bottom liquidity decile.[9]

[9] We only compare the top and bottom liquidity deciles, as the variability in liquidity is quite low.

Table 8 presents the results for the top (Panel A) and bottom (Panel B) liquidity deciles. The estimated coefficients indicate that suspected EOD stock price manipulation has a statistically significant negative effect on innovation only for the top liquidity decile. The magnitude of the effect in the top liquidity decile is almost four (seven) times higher for the number of patents (citations). This suggests that for the most liquid stocks, EOD stock price manipulation is particularly harmful to innovation.

[Table 8 here]

5.5. Intellectual Property Rights and EOD Stock Price Manipulation

In this subsection, we test the predictions that the negative association between EOD stock price manipulation and innovation would be more pronounced in countries with lower levels of intellectual property rights protection (predictions discussed in Section 2.2). To test these predictions, we split our sample between firms traded in high- and low-IPR environments. High- (low-) IPR environment firms are traded on markets where the IPR index is higher than (lower than or equal to) the mean. The results are presented in Table 9. Panel A presents the results for high-IPR firms and Panel B for low-IPR firms. As expected, in high-IPR environments, the EOD_DUMMY has no significant effect on the three innovation measures. In Panel B, the results indicate that the EOD_DUMMY has a negative and statistically significant effect on innovation at the 1% level in low-IPR environments. The magnitude of this effect is almost twice that for the number of patents. These results highlight the importance of intellectual property rights in curbing the negative effects of market manipulation.

[Table 9 here]

5.6. Shareholder Protection Rights and EOD Stock Price Manipulation

In this subsection, we test the predictions that the negative association between EOD stock price manipulation and innovation would be more pronounced in countries with weak shareholder protection rights (predictions discussed in Section 2.3). We test these predictions by splitting the sample into high and low shareholder protection rights environment subsamples. High- (low-) SPR firms are traded on markets that have an SPR index higher than (lower than or equal to) the mean. The results are presented in Table 10. Panel A presents the results for high-SPR firms and Panel B for low-SPR firms. As expected, in low-SPR environments, the EOD_DUMMY has no significant effect on the three innovation measures. In Panel A, the results indicate that the EOD_DUMMY has a negative and statistically significant effect on innovation at the 1% to 5% level in high-SPR environments. These results confirm our expectations.

[Table 10 here]

5.7. Additional Analysis

In untabulated results, we also test whether our results hold for other subsamples of data, measurement issues, endogeneity, and regression model specifications. Consistent with the full sample results, we find that the results hold for the non-U.S. and U.S. subsamples. We also test whether the results remain robust if we exclude or only include the global financial crisis period from August 2007 to December 2008. The findings are consistent. We then verify whether our results are robust to using different measures of innovation subsets of applied and granted patents (Table A2 in the Appendix), including adjustments for the truncation bias, survivor bias, and winsorizing, respectively. The results remain consistent with those reported in the paper.

The EOD stock price manipulations can be in either direction. We therefore test if the direction of EOD stock price manipulation matters. In untabulated analysis, we find that both downwards and upwards EOD stock price manipulation has a negative effect on innovation.

We also consider other variables such as price informativeness (Ding, 2015; Mathers et al., 2017), and other law and finance variables pertaining to, for example, creditor rights and enforcement rights.[10] We found no material differences from the results reported herein. Our results also show that our findings are not attributable to "bad" firms innovating less and manipulating more, since the average firm subjected to manipulation in the sample is more

[10] To proxy for stock price informativeness, we compute price nonsynchronicity for each firm-year as a logistic transformation of one minus the R2 from the Fama-French (1993) three-factor model. To measure creditor rights, we use the creditor rights index based on La Porta et al., 1998. The enforcement rights are measured using La Porta, et al. (1998).

innovative during the pre-manipulation period. It is possible that firms have located their innovative activity in certain countries due to tax incentives. Nevertheless, that should not affect our results, as we control for firm effects.

Levine et al. (2017) claim that enforcing insider trading laws has a positive effect on innovation. Using firm-level data, we predict that the effect of information leakage may, in fact, be positive or negative. On one hand, a positive effect could stem from the fact that insiders profiting from proprietary information may increase innovation (Agrawal and Cooper, 2015; Levine et al., 2017). On the other hand, we may expect negative effects due to equity misvaluations.

To illustrate, we use INFO_LEAK, which is a dummy variable equal to 1, if firm i experienced information leakage in year t, and 0 otherwise. The data are constructed as follows. The CMCRC and SMARTS first examine all news releases from the exchanges and then measure the return to the security over the six days prior to the announcement through the two days post-announcement. They double-check Thomson Reuters News Network to ensure 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 to the two days after the announcement. For each news announcement, a price movement is considered abnormal if it is 3 standard deviations away from the mean abnormal return during the 250-day benchmarking period, ending 10 days before the news release. To be included in our sample, the stock must have at least 150 days' worth of trading activities. We use a one-factor market model based on the market index for each exchange to calculate daily abnormal returns. To be included in the final dataset as a suspected information leakage case, the CAR around each event over the [t-6, t+2] period must be 3 standard deviations away from the normal nine-day CAR for each individual stock.

Once the suspected information leakage case is defined, we calculate abnormal profit per case as trading-volume-multiple abnormal returns from the period of six days before to one day before the news announcement. SMARTS surveillance staff independently examine the data to distinguish between market anticipation and suspected insider trading. Because SMARTS only classifies large movements that are 3 standard deviation changes away as insider trading, the possibility that insider trades could be viewed as market anticipation is mitigated.

The results are in Table A4 in the Appendix. The effect of INFO_LEAK has no significant effect on innovation measures (Panel A). In Panel B, we split INFO_LEAK into first-time

(INFO_LEAK_FIRST) and subsequent (INFO_LEAK_SUBSEQUENT) that indicate whether firm i: 1) did not previously experience EOD dislocation until year t, or 2) experienced information leakage before. The results show that INFO_LEAK_FIRST has a positive impact on innovation, while INFO_LEAK_ SUBSEQUENT has a negative effect on innovation. This is an interesting finding, because it shows positive effects of information leakage on innovation but only for firms that had not experienced information leakage before.

5.8. Limitations and Extensions

There are several limitations to our findings and possible opportunities for extension of this paper. We focus here on suspected EOD stock price manipulation, but there are other types of manipulation, such as wash trades, option backdating, and accounting fraud (see Cumming et al., 2015, for a survey). It is possible that EOD manipulation gives rise to and/or is correlated with other types of manipulation. We are unable to examine these types of manipulation within our sample for each country and year in the data. Future research using different data could shed more light on whether other manipulation types have a stronger impact on innovation.

6. Conclusion

This paper explores the impact of suspected EOD stock price market manipulation on the number of patents, the number of citations, and citations per patent based on a sample of nine countries spanning the 2003-2010 period. Our data indicate that EOD stock price dislocation decreases the number of patents and the citations received by patents, because of the associated short-termism of a firm's orientation, long-term damage to a firm's equity values, and reduced incentives for employees to innovate. Our findings are robust to numerous checks on subsamples of the data and on matching techniques for firms with and without dislocation, among other factors.

The data also confirm the importance of country-level factors, such as intellectual property rights and shareholder protection across countries. We find that, in an environment where intellectual property is protected, the adverse effects of EOD stock price manipulation have no consequence. The effect is negative and statistically significant only for firms in low shareholder protection markets.

References

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

Aghion, P., Bloom, N., Blundell, R., Griffith, R., Howitt, P., 2005. Competition and innovation: An inverted-U relationship. Quarterly Journal of Economics 120 (2), 701–728.

Aghion, P., Van Reenen, J. and Zingales, L., 2013. Innovation and institutional ownership. American Economic Review, 103(1), 277-304.

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

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

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

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

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

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

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

Amiram, D., Bozanic, Z., Cox, J.D., Dupont, Q., Karpoff, J.M., Sloan, R., 2018. Financial reporting fraud and other forms of misconduct: a multidisciplinary review of the literature. Review of Accounting Studies 23, 732–783.

Atanasov, V., Davies, R.J., Merrick, J.J., Jr., 2015. Financial Intermediaries in the Midst of Market Manipulation: Did They Protect the Fool or Help the Knave? Journal of Corporate Finance 34, 210–234.

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

Belloc, F., 2013. Law, finance and innovation: the dark side of shareholder protection. Cambridge Journal of Economics, 37(4), 863-888.

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

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

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

Blanco, I. and Wehrheim, D., 2017. The bright side of financial derivatives: Options trading and firm innovation. Journal of Financial Economics, 125(1), 99-119.

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

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

Borochin, P., Yang, J., 2017. The effects of institutional investor objectives on firm valuation and governance. Journal of Financial Economics 126, 171–199.

Borochin, P., Yang, J., Zhang, R., 2019. Common Ownership Types and Their Effects on Innovation and Competition. Available at: SSRN 3204767.

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

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

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

Bushee, B., 1998, The Influence of Institutional Investors on Myopic R&D Investment Behavior. Accounting Review 73, 305–333.

Bushee, B., 2001. Do Institutional Investors Prefer Near-Term Earnings over Long-run Value? Contemporary Accounting Research 18, 207–246.

Chapman-Davies, Adrian and Parwada, Jerry T. and Tan, Eric K. M., The Impact of Scandals on Mutual Fund Performance, Money Flows and Fees (July 29, 2014). UNSW Business School Research Paper No. 2014 BFIN 20.

Chau, C. and Aspris, A., Foley, S. and Malloch, H., 2019, Quote-Based Manipulation of Illiquid Benchmarks. Available at SSRN: https://ssrn.com/abstract=3560909

Comerton-Forde, C. and Putniņš, T.J., 2011. Measuring closing price manipulation. Journal of Financial Intermediation, 20(2), pp.135-158.

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

Cumming, D, Dai, N, 2010. Hedge fund regulation and misreported returns. European Financial Management 5, 829–857.

Cumming, D., Johan, S., Li, D., 2011. Exchange trading rules and stock market liquidity. Journal of Financial Economics 99 (3), 651–671.

Cumming, D., Walz, U., 2010. Private equity returns and disclosure around the world. Journal of International Business Studies 41 (4), 727–754.

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

Cumming, D., Ji, S., Johan, S. and Tarsalewska, M., 2020. End-of-Day Price Manipulation and M&As. British Journal of Management, 31(1), pp.184-205.

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

Danger, K., Flagge, M. and Outen, J., 2019. Market Manipulation Schemes at Option Expiration, Available at SSRN: https://ssrn.com/abstract=3520933.

du Plessis, M., Van Looy, B., Song, X., Magerman, T., 2009. Data Production Methods for Harmonized Patent Indicators: Assignee Sector Allocation. EUROSTAT Working Paper and Studies, Luxembourg.

Ederer, F. and Manso, G., 2013. Is pay for performance detrimental to innovation?. Management Science, 59(7), 1496-1513.

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

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

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

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

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

Hainmueller, J., 2012. Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. Political Analysis, 20, 25–46.

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

Hall, B.H., 2002. The financing of research and development. Oxford Review of Economic Policy 18, 35-51.

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

Hall, B.H., Lerner, J., 2010. The financing of R&D and innovation. Handbook of the Economics of Innovation 1, 609-639.

Himmelberg, C.P., Petersen, B.C., 1994. R&D and internal finance: A panel study of small firms in high-tech industries. Review of Economics and Statistics 76, 38-51.

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

Jarrow, R.A., 1992. Market manipulation, bubbles, corners, and short squeezes. Journal of Financial and Quantitative Analysis 27, 311-336.

Johan, S., Zhang, M., 2020. Information asymmetries in private equity: Reporting frequency, endowments, and governance. Journal of Business Ethics. In press.

Johnson, S., McMillan, J., Woodruff, C., 2002. Property rights and finance. American Economic Review 92, 1335-1356.

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

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

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

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

Kyle, A., Vila, J.-L., 1991. Noise trading and takeovers. RAND Journal of Economics 22, 54–71.

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

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

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

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

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

Leland, H.E., Pyle, D.H., 1977. Informational asymmetries, financial structure, and financial intermediation. Journal of Finance 32, 371-387.

Levine, R., 2005. Law, endowments and property rights. Journal of Economic Perspectives 19, 61-88.

Levine, R., Lin, C., Wei, L., 2017. Insider trading and innovation. Journal of Law and Economics 60 (4), 749–800.

Lin, Y., Michayluk, D., and Zou, M., 2019. Can Random Auction Ending Curb Market Manipulation? Available at SSRN: https://ssrn.com/abstract=3404507

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

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

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

Markovitch, Dmitri G., Joel H. Steckel, and Bernard Yeung. (2005): Using capital markets as market intelligence: Evidence from the pharmaceutical industry. *Management Science* 51 (10), 1467-1480.

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

Myers, S., Majluf N.S., (1984). Corporate financing and investment decisions when firms have information that investors do not have. Journal of Financial Economics 13 (2), 187-221.

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

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

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

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

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

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

Pirrong, C., 1999. The organization of financial exchange markets: Theory and evidence. Journal of Financial Markets, 2(4), 329-357.

Pirrong, C., 2004. Detecting manipulation in futures markets: The Ferruzzi soybean episode. American Law and Economics Review, 6(1), 28-71.

Rajan, R., Zingales, L. 1998. Financial dependence and growth. American Economic Review, 88 (3), 559–586.

Rosenbaum, P., Rubin, D., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70 (1), 41–55. doi: 10.1093/biomet/70.1.41.

Rosenbaum, P., Rubin, D., 1984. Reducing bias in observational studies using subclassification on the propensity score. Journal of the American Statistical Association 79 (387), 516–524.

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

Shen, C.H.H., Zhang, H., 2017. Tournament incentives and firm innovation. Review of Finance, 22 (4), 1515–1548.

Shleifer, A., Summers, L., 1988. Breach of trust in hostile takeovers, in A. J. Auerbach, ed.: Corporate Takeovers: Causes and Consequences (University of Chicago Press, Chicago).

Stein, J., 2003. Agency, information and corporate investment, in George Constantinides, Milton Harris, and Rene Stulz, eds.: Handbook of the Economics of Finance (North Holland, Amsterdam).

Vismara, S., Paleari, S., Signori, A., 2015. Changes in underwriters' selection of comparable firms pre- and post-IPO: Same bank, same company, different peers. Journal of Corporate Finance, 34, 235-250.

Table 1
Sample distribution
This table shows sample distributions by year (Panel A) and by country (Panel B) using a sample of public firms from Australia, Canada, China, India, Japan, New Zealand, Singapore, Sweden, and the U.S. Innovation measures are from 2004 to 2017. The EOD variables and the control variables are measured from 2003 to 2010. The sample size consists of 97,148 observations. Column (1) presents the total number of observations. Column (2) presents the number of EOD_DUMMY cases. Column (3) presents the frequency of EOD_DUMMY. All variables are as defined in the Appendix.

Panel A. Distribution by year

Year	N	EOD CASES	FREQ.
2003	9,844	2,216	23%
2004	10,062	2,637	26%
2005	11,169	2,394	21%
2006	12,425	2,462	20%
2007	12,889	2,815	22%
2008	13,507	3,066	23%
2009	13,642	3,178	23%
2010	13,610	2,770	20%
Total/Average	97,148	21,538	22%

Panel B. Distribution by country

Country	N	EOD CASES	FREQ.
Australia	11,136	1,786	16%
Canada	7 671	63	1%
China	6,876	421	6%
India	11,616	6,506	56%
Japan	20,911	2,066	10%
New Zealand	934	101	11%
Singapore	4,281	1,002	23%
Sweden	2,770	111	4%
United States	30,953	9,482	31%
Total/Average	97,148	21,538	22%

Table 2
Summary statistics
Summary statistics for the variables constructed using a sample of public firms from Australia, Canada, China, India, Japan, New Zealand, Singapore, Sweden, and the U.S. Innovation measures are from 2004 to 2017. The EOD variables and the control variables are measured from 2003 to 2010. The sample size consists of 97,148 observations. All variables are as defined in the Appendix.

Description	Mean	SD	25th percentile	Median	75th percentile
INNOV_PAT	0.418	1.074	0.000	0.000	0.000
INNOV_PAT_GRNT_ADJ	0.335	0.944	0.000	0.000	0.000
INNOV_CITE	0.480	1.507	0.000	0.000	0.000
INNOV_PAT_CHANGE	-0.009	0.365	0.000	0.000	0.000
INNOV_CITE/ PAT	0.192	0.665	0.000	0.000	0.000
EOD_DUMMY	0.222	0.415	0.000	0.000	0.000
EOD_COUNT	0.545	1.257	0.000	0.000	0.000
EOD_DUMMY_FIRST	0.079	0.270	0.000	0.000	0.000
EOD_DUMMY_SUBSEQUENT	0.143	0.350	0.000	0.000	0.000
MKTVOL	0.008	0.005	0.004	0.006	0.010
LIQUIDITY	3.463	4.396	-0.027	4.137	6.870
MV	6.648	2.936	4.445	6.670	8.759
ROA	-0.064	0.374	-0.025	0.020	0.059
RDTA	0.030	0.245	0.000	0.000	0.007
PPETA	0.294	0.260	0.066	0.231	0.460
LEV	0.216	0.225	0.013	0.162	0.344
CAPEXTA	0.058	0.085	0.008	0.028	0.068
TOBIN Q	1.661	2.583	0.622	0.976	1.673
IPR	7.394	1.455	7.600	8.000	8.200

Table 3

EOD manipulation and innovation quantity

This table presents OLS panel regressions for the dependent variable INNOV_PAT. We present the regression coefficients of estimating Eq. (1). Column (1) shows the results, where the suspected EOD manipulation is measured as a dummy variable (EOD_DUMMY), Column (2) as a count (EOD_COUNT), and, in Column (3), where suspected EOD stock price manipulations are split into first-time (EOD_DUMMY_FIRST) and subsequent (EOD_DUMMY_SUBSEQUENT). Each model includes a set of control variables and firm and year fixed effects. Standard errors are clustered by firm. All variables are as defined in the Appendix. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

	(1)		(2)		(3)	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0072*	[-1.86]				
EOD_COUNT			-0.0085***	[-5.27]		
EOD_DUMMY_FIRST					0.0044	[0.92]
EOD_DUMMY_SUBSEQUENT					-0.0173***	[-3.55]
MKTVOL	-4.7037***	[-7.11]	-4.5018***	[-6.82]	-4.7048***	[-7.11]
LIQUIDITY	0.0106***	[6.92]	0.0105***	[6.86]	0.0105***	[6.87]
MV	0.0096***	[3.34]	0.0104***	[3.61]	0.0098***	[3.42]
ROA	-0.0065*	[-1.65]	-0.0068*	[-1.73]	-0.0067*	[-1.70]
RDTA	0.0000	[0.01]	0.0000	[0.01]	0.0000	[0.02]
PPETA	0.0055	[0.53]	0.0054	[0.53]	0.0057	[0.55]
LEV	0.0256**	[2.07]	0.0265**	[2.14]	0.0263**	[2.13]
CAPEXTA	-0.0365**	[-2.43]	-0.0372**	[-2.48]	-0.0373**	[-2.48]
TOBIN Q	-0.0021***	[-2.76]	-0.0022***	[-2.89]	-0.0022***	[-2.81]
IPR	0.0739***	[8.45]	0.0785***	[8.90]	0.0749***	[8.56]
Firm fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
Obs.	97,148		97,148		97,148	
R2	0.926		0.926		0.926	

Table 4

EOD manipulation and innovation quality

This table presents OLS panel regressions for the dependent variable INNOV_CITE. We present the regression coefficients of estimating Eq. (1). Column (1) shows the results, where the suspected EOD manipulation is measured as a dummy variable (EOD_DUMMY), Column (2) as a count (EOD_COUNT), and, in Column (3), where suspected EOD stock price manipulations are split into first-time (EOD_DUMMY_FIRST) and subsequent (EOD_DUMMY_SUBSEQUENT). Each model includes a set of control variables and firm and year fixed effects. Standard errors are clustered by firm. All variables are as defined in the Appendix. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

	(1)		(2)		(3)	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0284***	[-2.97]				
EOD_COUNT			-0.0332***	[-7.22]		
EOD_DUMMY_FIRST					0.0191	[1.61]
EOD_DUMMY_SUBSEQUENT					-0.0703***	[-5.54]
MKTVOL	-15.0106***	[-8.54]	-14.2325***	[-8.05]	-15.0155***	[-8.54]
LIQUIDITY	0.0181***	[5.38]	0.0177***	[5.26]	0.0177***	[5.28]
MV	0.0466***	[6.76]	0.0496***	[7.19]	0.0476***	[6.91]
ROA	-0.0340***	[-3.55]	-0.0352***	[-3.69]	-0.0347***	[-3.64]
RDTA	-0.0033	[-0.56]	-0.0033	[-0.57]	-0.0033	[-0.56]
PPETA	0.0317	[1.22]	0.0313	[1.21]	0.0325	[1.26]
LEV	0.0307	[0.88]	0.0339	[0.98]	0.0334	[0.96]
CAPEXTA	-0.1869***	[-5.58]	-0.1895***	[-5.66]	-0.1898***	[-5.67]
TOBIN Q	-0.0068***	[-4.17]	-0.0072***	[-4.43]	-0.0069***	[-4.27]
IPR	0.1645***	[10.07]	0.1819***	[11.23]	0.1685***	[10.35]
Firm fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
Obs.	97,148		97,148		97,148	
R2	0.773		0.773		0.773	

Table 5

EOD manipulation and innovation intensity

This table presents OLS panel regressions for the dependent variable INNOV_CITE/ PAT. We present the regression coefficients of estimating Eq. (1). Column (1) shows the results, where the suspected EOD manipulation is measured as a dummy variable (EOD_DUMMY), Column (2) as a count (EOD_COUNT), and, in Column (3), where suspected EOD stock price manipulations are split into first-time (EOD_DUMMY_FIRST) and subsequent (EOD_DUMMY_SUBSEQUENT). Each model includes a set of control variables and firm and year fixed effects. Standard errors are clustered by firm. All variables are as defined in the Appendix. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

	(1)		(2)		(3)	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0133**	[-2.38]				
EOD_COUNT			-0.0169***	[-6.94]		
EOD_DUMMY_ FIRST					0.0141*	[1.87]
EOD_DUMMY_ SUBSEQUENT					-0.0374***	[-5.11]
MKTVOL	-6.9323***	[-7.27]	-6.5215***	[-6.78]	-6.9352***	[-7.27]
LIQUIDITY	0.0080***	[4.19]	0.0078***	[4.08]	0.0078***	[4.08]
MV	0.0220***	[5.70]	0.0236***	[6.10]	0.0226***	[5.84]
ROA	-0.0132**	[-2.54]	-0.0138***	[-2.67]	-0.0136***	[-2.63]
RDTA	-0.0014	[-0.50]	-0.0014	[-0.51]	-0.0013	[-0.50]
PPETA	0.0032	[0.22]	0.0030	[0.21]	0.0037	[0.25]
LEV	0.0328*	[1.74]	0.0345*	[1.84]	0.0343*	[1.83]
CAPEXTA	-0.0896***	[-4.76]	-0.0909***	[-4.83]	-0.0913***	[-4.84]
TOBIN Q	-0.0033***	[-3.69]	-0.0035***	[-3.93]	-0.0034***	[-3.79]
IPR	0.0695***	[8.51]	0.0785***	[9.63]	0.0718***	[8.83]
Firm fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
Obs.	97,148		97,148		97,148	
R2	0.586		0.586		0.586	

Table 6

Effect of EOD on innovation: entropy balancing

In Panel A, we present the covariate balance for an entropy matched sample of firms with EOD stock price manipulation (Treated) and without EOD stock price manipulation (Control), based on firm characteristics, firm age (LNAGE), pre-innovation levels (L1INNOV_PAT), country, year, and industry. In Panels B, C, and D, we present the coefficients of estimating Eq. (1) using an OLS model for entropy matched samples, where the suspected EOD manipulation is measured as a dummy variable (EOD_DUMMY), as a count (EOD_COUNT), and where suspected EOD stock price manipulations are split into first-time (EOD_DUMMY_FIRST) and subsequent (EOD_DUMMY_SUBSEQUENT), respectively. In Panels B, C, and D, Column (1) shows the results, where the dependent variable is INNOV_PAT, Column (2) INNOV_CITE, and Column (3) INNOV_CITE/ PAT. Each model includes a set of control variables and firm and year fixed effects. Standard errors are clustered by firm. All variables are as defined in the Appendix. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

Panel A. Entropy balancing covariance balance

Dependent Variable	Treated (Mean)	Treated (Variance)	Control (Mean)	Control (Variance)
LNAGE	2.939	0.235	2.939	0.246
L1INNOV_PAT	0.411	1.148	0.411	1.148
MKTVOL	0.008	0.000	0.008	0.000
LIQUIDITY	4.126	12.230	4.126	14.970
MV	7.033	6.159	7.033	6.308
ROA	0.000	0.045	0.000	0.059
RDTA	0.030	0.012	0.030	0.102
PPETA	0.272	0.059	0.272	0.059
LEV	0.222	0.049	0.222	0.046
CAPEXTA	0.058	0.006	0.058	0.006
TOBIN Q	1.503	3.100	1.503	3.878
IPR	7.045	2.632	7.045	2.445

Panel B. Entropy balancing weighted regressions (EOD dummy)

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0086**	[-2.16]	-0.0343***	[-3.19]	-0.0155**	[-2.50]
MKTVOL	-3.5599***	[-4.33]	-24.6743***	[-9.13]	-11.0693***	[-8.07]
LIQUIDITY	0.0050**	[2.44]	0.0034	[0.65]	0.0001	[0.03]
MV	0.0201***	[4.86]	0.0889***	[7.65]	0.0465***	[7.45]
ROA	0.0001	[0.01]	-0.0021	[-0.07]	-0.0033	[-0.18]
RDTA	0.0013	[0.27]	-0.0243	[-1.32]	-0.0094	[-1.01]
PPETA	0.0205	[1.08]	0.0375	[0.65]	-0.0071	[-0.22]
LEV	0.0254	[1.12]	0.0087	[0.11]	0.0383	[0.92]

CAPEXTA	-0.0385*	[-1.72]	-0.1279**	[-2.24]	-0.0540*	[-1.72]
TOBIN Q	-0.0053***	[-2.77]	-0.0018	[-0.42]	-0.0025	[-0.96]
IPR	0.0143*	[1.69]	0.0726***	[4.38]	0.0345***	[4.12]
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	96,765		96,765		96,765	
R2	0.935		0.759		0.586	

Panel C. Entropy balancing weighted regressions (EOD count)

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_COUNT	-0.0062***	[-3.81]	-0.0217***	[-4.65]	-0.0109***	[-4.42]
MKTVOL	-3.4857***	[-4.22]	-24.4871***	[-8.95]	-10.9443***	[-7.89]
LIQUIDITY	0.0049**	[2.41]	0.0032	[0.62]	0.0000	[0.00]
MV	0.0205***	[4.95]	0.0902***	[7.74]	0.0473***	[7.56]
ROA	-0.0002	[-0.01]	-0.0029	[-0.10]	-0.0037	[-0.21]
RDTA	0.0014	[0.29]	-0.0240	[-1.32]	-0.0093	[-1.00]
PPETA	0.0210	[1.10]	0.0391	[0.68]	-0.0064	[-0.19]
LEV	0.0259	[1.14]	0.0101	[0.13]	0.0391	[0.94]
CAPEXTA	-0.0396*	[-1.77]	-0.1317**	[-2.30]	-0.0559*	[-1.78]
TOBIN Q	-0.0055***	[-2.83]	-0.0022	[-0.50]	-0.0027	[-1.03]
IPR	0.0178**	[2.06]	0.0845***	[4.98]	0.0405***	[4.69]
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	96,765		96,765		96,765	
R2	0.935		0.759		0.586	

Panel D. Entropy balancing weighted regressions (EOD first and subsequent)

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY_ FIRST	-0.0013	[-0.27]	-0.0234*	[-1.74]	-0.0059	[-0.73]
EOD_DUMMY_ SUBSEQUENT	-0.0144***	[-2.93]	-0.0428***	[-3.28]	-0.0230***	[-3.02]
MKTVOL	-3.5902***	[-4.38]	-24.7192***	[-9.17]	-11.1088***	[-8.12]
LIQUIDITY	0.0050**	[2.42]	0.0034	[0.64]	0.0001	[0.02]
MV	0.0202***	[4.89]	0.0891***	[7.66]	0.0467***	[7.47]
ROA	-0.0001	[-0.01]	-0.0024	[-0.08]	-0.0035	[-0.20]

RDTA	0.0013	[0.28]	-0.0242	[-1.32]	-0.0094	[-1.00]
PPETA	0.0214	[1.13]	0.0388	[0.68]	-0.0060	[-0.18]
LEV	0.0259	[1.14]	0.0095	[0.12]	0.0390	[0.93]
CAPEXTA	-0.0397*	[-1.77]	-0.1297**	[-2.27]	-0.0555*	[-1.77]
TOBIN Q	-0.0054***	[-2.80]	-0.0019	[-0.43]	-0.0026	[-0.98]
IPR	0.0144*	[1.69]	0.0727***	[4.38]	0.0345***	[4.13]
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	96,765		96,765		96,765	
R2	0.935		0.759		0.586	

Table 7
Effect of End-of-Month EOD manipulation on innovation
This table presents OLS panel regressions of estimating Eq. (1), where the EOD manipulation is measured as a dummy variable EOD_DUMMY_END in Panel A. Panel B and D in Column (1) shows the results, where the dependent variable is INNOV_PAT, Column (2) INNOV_CITE, and Column (3) INNOV_CITE/ PAT. Each model includes a set of control variables, as in previous models, and firm and year fixed effects. Standard errors are clustered by firm. All variables are as defined in the Appendix. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

Panel A. End-of-Month EOD Manipulation

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0137**	[-2.02]	-0.0636***	[-3.70]	-0.0251**	[-2.48]
Controls	Yes		Yes		Yes	
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	81,827		81,827		81,827	
R2	0.929		0.787		0.607	

Panel B. End-of-Month EOD Manipulation

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0064	[-1.61]	-0.0173*	[-1.70]	-0.0088	[-1.45]
EOD_DUMMY_END	-0.0027	[-0.46]	-0.0398**	[-2.54]	-0.0160*	[-1.69]
Controls	Yes		Yes		Yes	
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	90,272		90,272		90,272	
R2	0.926		0.773		0.586	

Table 8

EOD manipulation and innovation: Liquidity deciles

We present the regression coefficients of estimating Eq. (1), where the EOD manipulation is measured as a dummy variable (EOD_DUMMY). Column (1) shows the results where the dependent variable is INNOV_PAT, Column (2) INNOV_CITE, and Column (3) INNOV_CITE/ PAT. Each model includes a set of control variables, as in previous models, and firm and year fixed effects. Panel A shows the results for the sample of firms with stock liquidity in the top decile and Panel B for the bottom decile. Standard errors are clustered by firm. All variables are as defined in the Appendix. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

Panel A. Top decile of liquidity

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0311	[-1.56]	-0.2267***	[-4.68]	-0.1007***	[-3.98]
Controls	Yes		Yes		Yes	
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	9,714		9,714		9,714	
R2	0.963		0.877		0.712	

Panel B. Bottom decile of liquidity

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0055	[-0.39]	0.0108	[0.35]	0.0147	[0.70]
Controls	Yes		Yes		Yes	
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	9,714		9,714		9,714	
R2	0.770		0.567		0.609	

Table 9

EOD manipulation and innovation: Intellectual property rights

We present the regression coefficients of estimating Eq. (1), where the EOD manipulation is measured as a dummy variable (EOD_DUMMY). Column (1) shows the results, where the dependent variable is INNOV_PAT, Column (2) INNOV_CITE, and Column (3) INNOV_CITE/ PAT. Each model includes a set of control variables, as in previous models, and firm and year fixed effects. Panel A shows the results for the sample of firms with high intellectual property rights (above or equal the mean) and Panel B for the low intellectual property rights (below the mean). Standard errors are clustered by firm. All variables are as defined in the Appendix. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

Panel A. High intellectual property rights

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0013	[-0.23]	0.0080	[0.58]	0.0047	[0.57]
Controls	Yes		Yes		Yes	
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	59,303		59,303		59,303	
R2	0.937		0.792		0.605	

Panel B. Low intellectual property rights

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0147**	[-2.54]	-0.0291***	[-2.68]	-0.0165***	[-2.73]
Controls	Yes		Yes		Yes	
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	37,845		37,845		37,845	
R2	0.831		0.626		0.511	

Table 10

EOD manipulation and innovation: Shareholder rights index

We present the regression coefficients of estimating Eq. (1), where the EOD manipulation is measured as a dummy variable (EOD_DUMMY). Column (1) shows the results, where the dependent variable is INNOV_PAT, Column (2) INNOV_CITE, and Column (3) INNOV_CITE/ PAT. Each model includes a set of control variables, as in previous models, and firm and year fixed effects. Panel A shows the results for the sample of firms with a high shareholder rights index (above or equal the mean) and Panel B for the low shareholder rights index (below the mean). Standard errors are clustered by firm. All variables are as defined in the Appendix. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

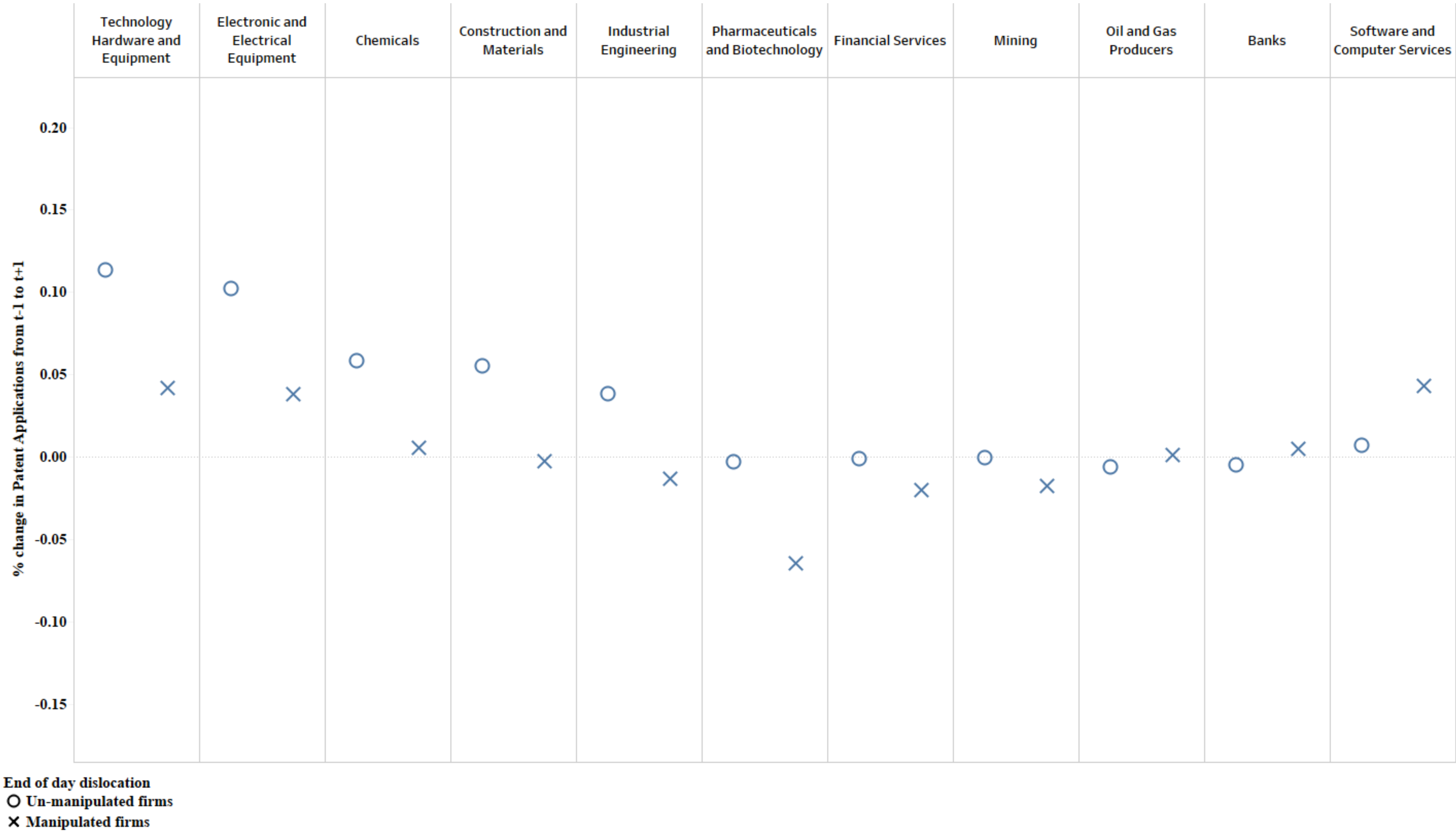
Panel A. High shareholder rights index

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0090**	[-2.08]	-0.0411***	[-3.82]	-0.0193***	[-3.08]
Controls	Yes		Yes		Yes	
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	82,308		82,308		82,308	
R2	0.926		0.775		0.587	

Panel B. Low shareholder rights index

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	0.0023	[0.44]	-0.0014	[-0.14]	0.0030	[0.44]
Controls	Yes		Yes		Yes	
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	14,840		14,840		14,840	
R2	0.796		0.572		0.448	

Fig. 1. This figure presents the percentage change in patent applications across sectors and EOD stock price manipulation. This figure compares the percentage of change in the number of patent applications from one period before the EOD manipulation (t-1) to one period after the EOD 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

Table A1
Variable definitions

Variable	**Definition**	**Data Source**
INNOV_PAT	The natural logarithm of 1 plus the total number of patents filed by firm *i* in year *t*+1.	PATSTAT
INNOV_CITE	The natural logarithm of 1 plus the total number of citations received by firm *i* for patents filed in year *t*+1. The number of citations is adjusted for truncation bias by using the citation lag distribution.	PATSTAT
INNOV_CITE/ PAT	The total number of citations received for patents filed in year *t*+1, divided by the total number of patents filed in year *t*+1.	PATSTAT
INNOV_PAT_GRNT_ADJ	The natural logarithm of 1 plus the total number of patents filed by firm *i* and subsequently granted, adjusted for truncation bias by using the grant lag distribution.	PATSTAT
INNOV_PAT_CHANGE	The difference between total number of patents filed in years *t*+1 and *t*-1, scaled by the total number of patents filed in year *t*-1.	PATSTAT
EOD_DUMMY	Indicates whether firm i has experienced EOD dislocation in year t The CMCRC and SMARTS surveillance staff constructed the dislocation of EOD price cases by examining price changes between the last trade price (P_t) and the last available trade price 15 minutes before the continuous trading period ends (P_{t-15}). For securities exchanges that have a closing auction, the close price at auction is used ($P_{auction}$). A price movement is dislocated if it is 4 standard deviations away from the mean price change during the benchmarking period for the past 100 trading days. To be considered a dislocation of EOD price case, at least 50% of the price dislocation must revert at open on the next trading day. Hence, the price movement between the last trade price (P_t) and the next day opening price (P_{t+1}) and between the last trade price (P_t) and the last available trade price 15 minutes before the	CMCRC

	continuous trading period ends (P_{t-15}) must be more than 50% ($P_{auction\ or}$ P_{t} - P_{t+1})/($P_{auction\ or}P_{t}$ - P_{t-15}) ≥50%. Sources: The Capital Markets Cooperative Research Centre (CMCRC) and SMARTS, Inc.	
EOD_DUMMY_FIRST	Indicates whether firm i has experienced EOD dislocation in year t, under the condition that firm i never previously experienced EOD dislocation until year t.	CMCRC
EOD_DUMMY_ SUBSEQUENT	Indicates whether firm i has experienced EOD price dislocation in year t, under the condition that it was manipulated before year t.	CMCRC
EOD_COUNT	The number of times a firm has experienced EOD price dislocation in year t, under the condition that it never previously experienced EOD price dislocation until year t.	CMCRC
EOD_DUMMY_STRONG	Dummy variable that equals 1, if firm i experienced EOD price dislocation in year t on days more likely to experience manipulation, and 0 otherwise. Manipulation is considered more likely during the last three trading days of a month.	CMCRC
EOD_DUMMY_WEAK	Dummy variable that equals 1, if firm i experienced EOD price dislocation in year t on days less likely to experience manipulation, and 0 otherwise. Manipulation is considered less likely on the days excluding the last three trading days of a month.	CMCRC
MKTVOL	The natural logarithm of the standard deviation of annual stock return distribution for every high/low index return of the most representative market index from each trading venue as these indices are already market cap weighted pair.	CMCRC
LIQUIDITY	Denotes the natural logarithm of the inverse of the AMIHUD illiquidity variable, computed as: $$A_{ij} = \frac{1}{D_{iy}} \sum_{i=1}^{D_{iy}} \frac{\lvert r_{it} \rvert}{Dvol_{it}},$$	Datastream

	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, and D_{iy} is the number of days with an available ratio in year y. A higher AMIHUD value indicates a higher level of illiquidity. Hence, the logarithm of the inverse of AMIHUD would be a measure of liquidity, rather than illiquidity.	
MV	Market value decile variable that takes a value of 1 to 10 based on the market value decile to which firm i belongs within each country-year grouping at the end-of-year t.	Datastream
ROA	Return on assets, defined as income before extraordinary items, divided by the book value of total assets, measured at the end of fiscal year t.	Datastream
RDTA	Research and development expenditures divided by the book value of total assets measured at the end of fiscal year t, set to 0 if missing.	Datastream
PPETA	Property, plant, and equipment divided by the book value of total assets measured at the end of fiscal year t.	Datastream
LEV	Firm i's leverage ratio, defined as the book value of debt, divided by the book value of total assets, measured at the end of fiscal year t.	Datastream
CAPEXTA	Capital expenditures scaled by the book value of total assets, measured at the end of fiscal year t.	Datastream
TOBIN Q	Firm i's market-to-book ratio during fiscal year t, calculated as the market value of equity, plus the book value of debt, divided by the book value of assets.	Datastream
FIRM_AGE	The natural logarithm of 1 plus firm *i*'s age, approximated by the number of years listed in Datastream.	Datastream
IPR_INDEX	Intellectual Property Rights Index, obtained from the International Property Rights Index Report published from 2007 to 2010. For	Property Right Alliance

	2003-2006, we use the oldest available index value from 2007.	
SPR_INDEX	The shareholder protection rights (SPR) index is formed based on shareholder protection rights variables defined by La Porta et al. (1998).	LLSV

Table A2

EOD manipulation and innovation quantity – Patent applications granted

This table presents OLS panel regressions for the dependent variable INNOV_PAT_GRNT_ADJ. We present the regression coefficients of estimating Eq. (1). Column (1) shows the results, where the suspected EOD manipulation is measured as a dummy variable (EOD_DUMMY), Column (2) as a count (EOD_COUNT), and, in Column (3), where suspected EOD stock price manipulations are split into first-time (EOD_DUMMY_FIRST) and subsequent (EOD_DUMMY_SUBSEQUENT). Each model includes a set of control variables and firm and year fixed effects. Standard errors are clustered by firm. All variables are as defined in the Appendix. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0080**	[-2.17]				
EOD_COUNT			-0.0054***	[-3.57]		
EOD_DUMMY_ FIRST					-0.0027	[-0.60]
EOD_DUMMY_ SUBSEQUEN					-0.0126***	[-2.70]
MKTVOL	2.8969***	[4.16]	2.9869***	[4.30]	2.8963***	[4.16]
LIQUIDITY	0.0091***	[6.27]	0.0090***	[6.23]	0.0091***	[6.25]
MV	0.0146***	[5.34]	0.0150***	[5.46]	0.0147***	[5.37]
ROA	-0.0114***	[-2.99]	-0.0116***	[-3.04]	-0.0115***	[-3.01]
RDTA	0.0055	[1.34]	0.0055	[1.34]	0.0055	[1.34]
PPETA	0.0008	[0.08]	0.0007	[0.08]	0.0009	[0.09]
LEV	0.0118	[1.04]	0.0123	[1.08]	0.0121	[1.07]
CAPEXTA	-0.0613***	[-4.07]	-0.0617***	[-4.09]	-0.0617***	[-4.09]
TOBIN Q	-0.0038***	[-5.17]	-0.0039***	[-5.24]	-0.0038***	[-5.19]

IPR	0.1492***	[16.31]	0.1519***	[16.50]	0.1497***	[16.36]
Firm fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
Obs.	97,148		97,148		97,148	
R2	0.897		0.897		0.897	

Table A3

EOD manipulation and change in innovation

This table presents OLS panel regressions for the dependent variable INNOV_PAT_CHANGE. We present the regression coefficients of estimating Eq. (1). Column (1) shows the results where the suspected EOD manipulation is measured as a dummy variable (EOD_DUMMY), Column (2) as a count (EOD_COUNT), and, in Column (3), where suspected EOD stock price manipulations are split into first-time (EOD_DUMMY_FIRST) and subsequent (EOD_DUMMY_SUBSEQUENT). Each model includes a set of control variables and firm and year fixed effects. Standard errors are clustered by firm. All variables are as defined in the Appendix. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

	(1)		(2)		(3)	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
EOD_DUMMY	-0.0070*	[-1.67]				
EOD_COUNT			-0.0039**	[-2.41]		
EOD_DUMMY_ FIRST					-0.0021	[-0.39]
EOD_DUMMY_ SUBSEQUENT					-0.0113**	[-2.10]
MKTVOL	-1.7655**	[-2.31]	-1.7146**	[-2.23]	-1.7661**	[-2.31]
LIQUIDITY	0.0010	[0.65]	0.0009	[0.61]	0.0009	[0.62]
MV	-0.0003	[-0.11]	-0.0001	[-0.04]	-0.0002	[-0.07]
ROA	0.0138***	[2.79]	0.0137***	[2.77]	0.0137***	[2.78]
RDTA	-0.0065	[-1.22]	-0.0065	[-1.22]	-0.0065	[-1.22]
PPETA	-0.0056	[-0.61]	-0.0057	[-0.61]	-0.0056	[-0.60]
LEV	-0.0095	[-0.78]	-0.0092	[-0.76]	-0.0092	[-0.76]
CAPEXTA	0.0028	[0.16]	0.0025	[0.15]	0.0025	[0.15]
TOBIN Q	0.0015*	[1.86]	0.0015*	[1.83]	0.0015*	[1.85]

IPR	0.0093	[1.38]	0.0111	[1.64]	0.0098	[1.44]
Firm fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
Obs.	97,148		97,148		97,148	
R2	0.150		0.150		0.150	

Table A4

Information leakage and innovation

We present the regression coefficients of estimating Eq. (1), where insider trading is measured as a dummy variable (INFO_LEAK) in Panel A, and, in Panel B, we split information leakage into first-time (INFO_LEAK_FIRST) and subsequent (INFO_LEAK_SUBSEQUENT). Column (1) shows the results where the dependent variable is INNOV_PAT, Column (2) INNOV_CITE, and Column (3) INNOV_CITE/ PAT. Each model includes a set of control variables, as in previous models, and firm and year fixed effects. Standard errors are clustered by firm. All variables are as defined in the Appendix. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

Panel A. Information leakage: All

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
INFO_LEAK	-0.0050	[-0.99]	0.0216*	[1.73]	0.0089	[1.18]
Controls	Yes		Yes		Yes	
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	97,148		97,148		97,148	
R2	0.926		0.897		0.586	

Panel B. Information leakage: First and subsequent

	(1) INNOV_PAT		(2) INNOV_CITE		(3) INNOV_CITE/ PAT	
Dependent Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
INFO_LEAK_ FIRST	0.0033	[0.55]	0.0409***	[2.95]	0.0207**	[2.33]
INFO_LEAK_ SUBSEQUENT	-0.0191***	[-2.61]	-0.0117	[-0.59]	-0.0113	[-1.02]
Controls	Yes		Yes		Yes	
Firm FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Obs.	97,148		97,148		97,148	
R2	0.926		0.897		0.586	