EMPIRICAL ESSAYS ON FINANCE AND INNOVATION

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ABSTRACT

This dissertation consists of three empirical studies in finance and innovation. I study various financial factors affecting innovation such as stock market manipulation and public to private transaction. I also investigate the effect of ownership structure on these public to private transactions.

The first study finds that the End-of-day price manipulation is associated with short-termism of the firm's orientation, long-term harm to a firm's equity values, and commensurate with reduced incentives for employees to innovate. Insider trading, by contrast, enables innovators to achieve exacerbated profits from innovation. Using a sample of suspected manipulation events for all stocks from nine countries over the years 2003-2010, I find evidence consistent with these real impacts of market manipulation on innovation. These findings are not attributable to "bad" firms innovating less and manipulating more, since the average firm subjected to manipulation in the sample is more innovative during the pre-manipulation period.

The second study investigates the effect of going private buyout transactions on the investments in innovation using an international sample of buyout transactions from 36 countries over 1997 to 2011. Patent counts and citations are used to proxy for quantity, quality and economic importance of innovation. The data indicate that the effect of buyouts on innovation is quite sizable in terms of quantity and quality, as both patent counts and citations drop following a buyout. I also find that the number of radical patents (i.e. more scientific) drop as well. When we split the sample into institutional and management buyouts the negative association is only confirmed for institutional buyouts. We find that the negative effect of buyouts on innovation is aggravated in

post-2006 period, suggesting that the nature of deals has worsened for innovation over time. The data also show that buyouts have a negative effect on innovation efficiency.

The third study considers ownership structure of target firms that are subject to going private buyout transactions, which are often highly leveraged and give rise to potential agency conflicts among existing shareholders. In this study, I examine ownership structure prior to going private transactions in 33 countries around the world from 2002 to 2014.The data indicate strong and consistent evidence that pre-going private ownership is characterized by higher institutional and corporate ownership. Family ownership lowers the probability of a public to private transaction. Stronger creditor rights increase the probability of going private particularly for whole company and institutional buyouts.

To my lovely wife and my parents.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

Introduction

This dissertation contributes to the fields of innovation and finance. Considering the increasingly competitive environment within which firms operate, innovation is critical in ensuring that firms can differentiate themselves from their competitors. In a knowledge based global economy, governments around the world are also placing a strong emphasis on innovation output and efficiency. Since innovative projects are both risky and capital intensive, a developed financial sector plays an important role in the innovation process (Amore et al., 2013; Laeven et al., 2015). Previous studies have looked at various financial factors that impact innovation such as banking deregulation (Chava et al., 2013), institutional ownership (Aghion et al., 2013) and stock liquidity (Fang et al., 2014).

This dissertation comprises of three essays. The first two essays contribute to the innovation and finance literature by identifying additional factors such as stock market manipulation and public to private transactions, which have an impact on the quantity and quality of innovation. In the third essay, the dissertation delves further into public to private transactions and identifies ownership structure as having a significant impact on the decision to go private.

In the first study we investigate whether stock market manipulation affects innovation. We hypothesize that a company whose stock is subject to a high degree of manipulation would have increased incentives to focus on short term factors at the cost of long term investments such as in innovation. When the determinants of stock prices are influenced by non-fundamental factors such as manipulation, the managers of these companies would have less of an incentive to focus on long term investments in R&D that increase the fundamental value of the companies.

Most studies on market manipulation have focused on the financial impact of manipulation. For example, Cumming, Johan, & Li (2011) looked at how the exchange trading rules pertaining to market manipulation, over time and across markets, significantly affects liquidity. Aggarwal & Wu (2006) examine stock market manipulations and its implications for stock market efficiency. However, there have been no studies that consider the effect of stock market manipulation on real investments such as in innovation.

The effects of financial market misconduct have been widely studied because the potential consequences can be dire. In this paper, we identify reduced innovative activity as an additional consequence to financial market misconduct. This is a result and study that has not been performed before. The study is an international one and we analyze whether there firms that get manipulated or whose management engages in Insider trading will subsequently have reduced incentives to innovate.

Why do we think that manipulation affects innovation? The link between manipulation and innovation is not immediately evident – one may wonder why a manipulated firm's scientist would behave any differently or innovate any less than the scientist in a competing non-manipulated firm. However, the presence of manipulation is strongly associated with short-termist behavior. Ferreira et al. (2014) has observed that public companies have strong incentives to focus on short term projects because good news is usually very quickly incorporated into the valuation of the company. A public company that is being constantly manipulated, whether the manipulation is positive or negative, is likely to have an exacerbated negative effect on innovation. If the manipulation leads to negative prices, there would be strong incentives for the management to engage in short term projects in order to infuse some good news into the market and help push the prices up. On the other hand, if manipulation leads to higher equity prices, then the management would have to take on projects that would provide support for this over-valuation. This is more likely to be short term projects with an immediate payoff.

Manipulation is also likely to negatively affect long term equity values – this would have a negative effect on scientists who may be holding equity options in the company. According to Chang et al. (2015) employee stock options have a positive effect on innovation. However, when employee stock options are coupled with managerial manipulation of stock prices, Zhang et al. (2008) find that this leads to incentive misalignment.

Market manipulation may also negatively affect innovation by increasing information asymmetry and an associated increase in cost of capital. According to Hirshleifer, Hsu, & Li (2012) information about prospects of new innovations are especially hard to process and on average there will be positive (negative) abnormal returns after good (bad) news related to prospects for firms' innovation. Aboody & Lev (2000) identified R&D intensity as a major source of information asymmetry which lead to larger insider trading gains. This information asymmetry associated with innovation is further exacerbated by the presence of manipulators who make information seekers (arbitrageurs) less effective at ferreting out information about the firm's prospects (Allen and Gale 1992). Aggarwal & Wu (2006) find that increasing the number of information seekers may worsen market efficiency when there are manipulators present.

On the other hand, manipulation may enhance the gains to insiders from innovation, which would, in turn, increase the incentives for managers to innovate. The link between market manipulation and innovation is ambiguous in theory, and one must, therefore, look to data to ascertain the validity of the connection between manipulation and innovation.

PATSTAT provides an international patent dataset for 92 countries with firm level data on the number of patents applied, patents granted and citations. It contains basic bibliographic information on patents, including the identity number of the application and granted patent, the date of the patent application, the date when the patent is granted, the track record of patent citations and inventor identification for each patent application. The PATSTAT database is published biannually and we use the 2014 Autumn edition.

This study covers 11 stock exchanges from nine countries from 2003 to 2010. The sample includes the Australian Securities Exchange, TSX Venture Exchange, Shanghai Stock Exchange, Bombay Stock Exchange, National Stock Exchange of India Ltd., Tokyo Stock Exchange, New Zealand Stock Exchange, Singapore Exchange, Stockholm Stock Exchange, Nasdaq Stock Market and New York Stock Exchange.

We construct a dataset of the frequency and severity of various kinds of manipulations (such as the end of day manipulation measure used in Aitken, Cumming, & Zhan (2015a, 2015b)). We use two measures of manipulation: 1) end-of-day price dislocation (EOD), and 2) information leakage (infoleakage) alerts computed by the CMCRC and SMARTS surveillance staff. Next, we relate the frequency and severity of different types of market manipulations across markets and over time to various measures of innovation such as the number of patents and number of citations. In addition, this study matches firm-specific manipulation data with firm-specific innovation data to carry out more direct tests of whether manipulation affects innovation.

In the second study, we investigate the effects of public to private buyout transactions (also known as a going private transaction) on investments in innovation using an international sample of buyout transactions from 1997 to 2011. This study makes a distinction between institutional and management buyouts, and between patents that are radical in nature and those that are incremental.

There have been various studies on the effect of Private Equity and Leveraged Buyouts (LBO) on firm's financial and accounting performance. Cumming el al. (2007) reviews this literature and finds that in general performance of companies that experience buyouts improve following the buyout transaction. Desbrieres and Schatt (2002) find that following private equity buyouts, firms' improve their accounting performance compared to similar firms that did not have a buyout transaction. Groh and Gottschalg (2006) find that the financial performance of buyout firms is higher compared to the control group of firms.

There have also been numerous studies that analyzed the effect of buyouts on real factors such as productivity. Lichtenberg and Siegel (1990) analyzed data from the US Census Bureau's Longitudinal Research Database (LRD) that contains information about 19,000 large US manufacturing plants for the years 1972-1988, and found that plants that had a management buyout had higher total factor productivity (TFP) compared to similar plants in the same industry that did not experience a management buyout. Lerner et al. (2011) analyzed the patenting behavior of 472 US firms after being part of a private equity transaction. They find that firms' patenting activity accelerates following private equity buyouts. They also find that firms are more focused on their patenting activity following these type of transactions – and they tend to innovate more in technology fields in which they have focused historically. They focus entirely on private equity transactions that have been funded through substantial amount of debt, which are referred to as Leveraged Buyouts (LBOs).

My study differs from Lerner's in many important aspects. First, theirs is solely US based, while my study has an international scope and incorporates data from 36 countries. Second, their study only considers Private Equity buyout transactions that are associated with a substantial amount of indebtedness, while my study considers several types of public to private buyout transactions such as management buyouts and institutional buyouts (of which Leveraged Private Equity buyouts is a subset). Finally, their study does not make a distinction between radical and incremental patents, while my study uses an intuitive measure that distinguishes between these two types of innovation.

Institutional buyouts refer to those buyouts where a Private Equity firm has taken a 50% stake or more in the target company or is the parent of the acquirer. The acquisition often takes place through a 'new company' (newco) or an acquisition vehicle. Management buyouts refer to those buyouts where the Management of the company buys at least 50% of the company from its existing owners. A private equity company is sometimes brought in to aid the purchase through provision of equity funding. A 'new company' (newco) is normally formed by the management team specifically to purchase the Target.

We stipulate that institutional investors might have different incentives and long-term policies than management. It is often claimed that institutional buyouts by Private Equity firms have a shorter time horizon and hence, their objective is to restructure the company in a way that provides short term benefits at the cost of long term objectives such as innovation. If this view holds, then we would expect to see a drop in the quantity and quality of innovation following the Institutional buyout transactions.

Not all patents are made the same and the importance of patents is another important dimension to consider while studying innovative activity. Previous studies on innovation has used citation counts and measures such as "Generality" and "Originality" to measure the quality and content of the patents. We propose an intuitive measure that uses Non-Patent literature to distinguish between radical and incremental patents. Patents are segregated into radical and incremental innovations similar to Griffith and Macartney (2014). If a patent has at least one citation to Non-Patent literature (NPL), we consider that patent as a radical innovation. NPL generally refers to scientific journals and therefore, patents making citations to NPL are likely to be new and radical innovation.

We collect buyout transactions from Zephyr database. Only deals where the acquirer bought 100% of the target firm are considered. We include all completed buyout transactions from 1997 to 2011 (we need three years post buyout on patents) from 36 countries. We choose only buyout deals where the target firm had at least one successful patent applied for and granted from 3 years before the transaction and to 3 years afterwards (similar to Lerner et al., 2011). Like the first study, the patent data is derived from EPO's Worldwide Patent Statistical Database (PATSTAT). We are using the 2014 Autumn edition of this database.

The main measure of innovation used in the paper is the number of citations received by patents. The number of patents applied for and granted is also used as a measure of innovation. Two separate measures of patent citations are used in the paper. The first measure, Citation count, considers all the citations received by a patent from the grant date onwards. The second measure, Absolute citation count, consider only the citations made within the three-year period, starting from the year of grant of the patent to 3 years following the grant date. The Absolute citation measure mitigates the issue of truncation towards the end of the sample.

Due to the count nature of the innovation variables, we initially considered using the Poisson model. However, like other studies using patent data, we find over-dispersion in our main dependent variables and thus we decided to use the negative binomial model instead. The main independent variables of the model are year dummies of the patent filing relative to the buyout year.

In the third study, we examine the ownership structure prior to going private transactions in 33 countries around the world from 2002 to 2014, with the aim of identifying whether ownership structure impacts the decision of going private. Since most of the going private transactions are highly leveraged, and involve potential agency conflicts among existing shareholders, we hypothesize that ownership structure should have a significant effect on the decision to go private. We consider three types of ownership structures in the study, those characterized by higher institutional, corporate or family ownership. In addition, we also study the impact of creditor rights and legal conditions on the decision to go private.

This study analyzes whether there are substantial differences between firms' ownership structure prior to the going private transaction. We hypothesize that firms with certain ownership structure would be more likely to be taken private. Different types of owners would have different objectives and incentives on how they affect the firm's policies, how they are affected by a decision to sell the firm and how they engage in the management of the firm. To identify different types of ownership structures, we consider the percentage ownership as well as block ownership by corporate, institutional and family owners. We expect that the agency problems are more severe when a greater percentage of the firm is controlled by corporate or institutional shareholders and it is possible to have more gains from public to private transactions in this case. In addition, the corporate and institutional investors have a shorter investment horizon when compared to family owners, and they would be more interested in an exit through a public to private transaction. Family owners, on the other hand typically have a tighter control over the management team and face fewer agency problems. They also usually have a longer investment horizon. These factors make it less likely that firms with family ownership experience a public to private transaction.

In addition, the fashion in which a firm is taken private might also differ. We consider the following types of public to private buyouts – whole firm buyouts, buildup strategy buyouts, management buyouts and institutional buyouts. In the case of whole firm buyout, the public to private transaction occurs as a single event, whereas in the case of a build up strategy the transaction is completed in several stages.

A public to private transaction is termed as an institutional buyout if a Private Equity firm takes a majority stake in the target company or is the parent of the acquirer, whereas in a management buyout the existing management of the company buys at least 50% of the company from its existing owners.

Institutional ownership is computed based on the ownership that is held by institutional investors such as private equity, banks, venture capital etc. Corporate ownership is the percentage of ownership held by an industrial company. Family ownership is based on the percentage of ownership by family. Block ownership is defined as the case where a single type of owner has more than 10% of the ownership of a company.

We also study the effects of creditor rights and legal conditions on the likelihood of going private, for different types of buyouts. It is likely that stronger creditor rights increase the probability of going private.

Chapter 2

Market Manipulation and Innovation

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

2.1. Introduction

Stock market volatility has been shown to redirect management towards short-term planning, which in turn influences R&D and marketing budgets (Chakravarty and Grewal, 2011). In this paper, we extend this notion to examine a link between stock market manipulation and R&D outcomes in the form of patents and patent citations.

Financial market misconduct comes in a variety of forms. Two of the most commonly observed (and, therefore, commonly studied) forms of manipulation include insider trading (Allen and Gale, 1992; Allen and Gorton, 1992; Meulbrook, 1992; Bebchuk and Fershtman, 1994; Agrawal and Cooper, 2015; Bernilie et al., 2015; Aitken et al., 2015b) and end-of-day manipulation (Atanasov et al., 2015; Aitken et al., 2015a). It is well known that when there is information only known by insiders, they can trade in advance of public dissemination of the information for short-term profit at the expense of the counterparties in the trade and at the expense of the long-term value to the firm. It is perhaps somewhat less well known that there are massive

[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

incentives to manipulate closing price by ramping up end-of-day trading to push the closing price to an artificially high level. End-of-day prices are used to determine the expiration value of derivative instruments and directors' options, determine the price of seasoned equity issues, evaluate broker performance, compute net asset values of mutual funds, and compute stock indices (Aitken et al., 2015).[2]

In theory, there are different perspectives on whether or not market manipulation should enhance or mitigate innovation. On one hand, the presence of market manipulation is associated with short-termism of the firm's orientation, which is inconsistent with a long-term managerial focus on innovation. Over- or under-valuation of a firm's equity causes agency problems (Jensen, 2005; Marciukaityte and Varma, 2008), and in turn agency problems impede innovation (Manso, 2011). Also, market manipulation imposes long-term harm to a firm's equity values and commensurate reduced incentives for employees to innovate. Ferreira et al. (2014) find that public firms have fewer incentives when exploring radical new innovations, because the rapid incorporation of good news into market prices creates incentives for short-termist behavior. Bereskin et al. (2014) find that firms engaging in managerial manipulation of R&D expenditures have reduced levels of firm innovation. Market manipulation may be yet another reason for why public firms innovate less and have more incentives for short-termist behavior. On the other hand, manipulation may enhance the gains to insiders from innovation, which would, in turn, increase the incentives for managers to innovate. The link between market manipulation and innovation is

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

ambiguous in theory, and one must, therefore, look to data to ascertain the validity of the connection between manipulation and innovation.

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

The data examined in this paper indicate that end-of-day dislocation mitigates patents, and we argue that this evidence is consistent with the notion that manipulation is associated with short-termism of the firm's orientation, long-term harm to a firm's equity values, and commensurate with reduced incentives for employees to innovate. The economic significance of this effect is greater when dislocation occurs on days when dislocation is more likely to be attributable to manipulation, such as at the end of the month, quarter, and/or year. The data indicate that end-of-day dislocation has a pronounced negative impact on patenting, even after controlling for other market efficiency variables such as liquidity, among other factors. The economic significance is such that the presence of end-of-day dislocation mitigates a subsequent year's patenting by 7.3%. Estimated differently, a 1-standard deviation increase in the number of dislocation events in one year is associated with a 1.9% reduction in patenting during the subsequent year.

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

One possible concern with the connection between innovation and manipulation is that "bad" firms are more likely to be associated with manipulation, and "bad" firms are less likely to innovate. If this is the case, a finding that firms with manipulated stock prices patent less is not particularly surprising, because both are symptomatic of firms being bad-type firms; put differently, the effect may be a selection effect versus a treatment effect. We can rule out this explanation at the outset, since, in our sample, we observe that in the period prior to end-of-day manipulation, firms that are manipulated have 0.43 patents on average, compared to 0.39 patents for those that do not face end-of-day manipulation. Similarly, in the period prior to information leakage, firms that have information leakage have 0.95 patents on average, compared to 0.35 patents for those without information leakage. Therefore, the data do not support a connection between manipulation and innovation due to a third unobservable "bad quality" variable. We provide a variety of propensity score matching techniques and other checks to examine the change in patents from the pre-manipulation to post-manipulation period to establish a causal connection between manipulation and innovation and explicitly show the treatment estimates (Table 2.10, below).

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

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

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

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

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

This paper is organized as follows: Section 2 discusses the economic link between market manipulation and innovation. Section 3 presents the data. Section 4 provides univariate tests of the relation between market manipulation and patents. Multivariate analyses are presented in Section 5. Limitations and extensions are discussed in Section 6. The final section offers concluding remarks. Additional robustness tests are provided in the Appendices as well as in an accompanying Online Appendix.

2.2. Economic Link between Market Manipulation and Innovation

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

Table 2.1 summarizes the economic causal link between market manipulation market, in a microstructure sense, and innovation. At first glance, the link between market microstructure an innovation, normally two very distinct fields, may seem unusual, but there is a stream of literature that connects market liquidity to innovation (e.g., Fang et al., 2014); therefore, this paper is not the first to make the connection. The innovation here is to change the analysis of liquidity (e.g., bid-ask spreads) and instead focus on market manipulation. Arguably, as manipulation and fraud can have substantial consequences for a firm with respect to a firm's long-term economic outcomes (Karpoff et al., 2008a,b, 2012), it is natural to focus on market manipulation and not see the other microstructure properties of a firm's stock, such as its liquidity. It is widely regarded that governance affects innovation (Ayyagari et al., 2011, 2014; O'Connor and Rafferty 2012; Chen et al., 2014; Lyandres and Palazzo, 2016; Yung, 2016), and here, we are extending the governance impact to an analysis of market misconduct.

[Table 2.1 here]

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

Table 2.1 consists of two panels: Panel A lists the first-order effects connecting manipulation to innovation. Over- or under-valuation of a firm's equity gives rise to severe agency problems insofar as managers have short-term pressures to manipulate information released to the public to justify the improper valuation (Jensen, 2005; Marciukaityte and Varma, 2008), and in turn there agency problems and short-term perspectives impede innovation (Manso, 2011). Manipulation damages long-term equity values (Aggarwal and Wu, 2006; Karpoff et al., 2008a,b; Dyck and Zingales, 2010; Agrawal and Cooper, 2015; Aitken et al., 2015a,b). The reduced long-term prospects for a firm worsen its ability to raise future equity (Brown et al., 2009, 2013) and shift the focus of a firm's management to short-termism and short-term pay structures (Peng and Röell, 2014). The short-term focus of the firm is inconsistent with long-term innovation outcomes, as innovation requires a long-term horizon (Manso, 2011) and incentive pay (Shen and Zhang, 2017). Therefore, in general, we expect manipulation -- such as that of end-of-day manipulation -- to negatively impact innovation. As well, we note that it does not matter who is actually responsible for the end-of-day manipulation in terms of either insiders or outsiders, as the effects summarized in Table 2.1 all point in the same direction that it will have a negative impact on a firm's innovation.

There is a caveat with respect to the impact of information leakage and insider trading on innovation that is distinct from end-of-day manipulation and innovation. Specifically, insiders may take advantage of the knowledge of innovation and trade in advance of the announcement of an innovation (see also Agrawal and Cooper, 2015; Levine, 2015). The ability of insiders to profit off of the inside knowledge of an innovation announcement may lead to exacerbated profits for insiders and inspire a firm with wrongdoers as insiders to pursue more innovation. While advance knowledge about innovations would not be the only informational advantage held by insiders – we still believe that information on innovation would be particularly valuable to anyone engaged in insider trading because this information can have a large impact on the long term growth and valuation of the company. If this effect outweighs the other effects, it is possible that a firm with frequent and pronounced information leakage has more innovation.

Our two hypotheses are, therefore, as follows:

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

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

Table 2.1, Panel B lists three second-order effects. First, stock price informativeness is a second-order effect insofar as end-of-day manipulation (insider trading) lowers (raises) stock price informativeness which, in turn, reduces (raises) information leakage to competing firms and thereby reduces (increases) incentives for firms to invest in innovation (see the model of Ding, 2015, for complete details). Second, both end-of-day price manipulation and insider trading reduce liquidity, in line with the close connection between manipulation, price accuracy, and liquidity proposed by Kyle and Viswanathan (2008). A reduction in liquidity, in turn, may have a positive effect on innovation, if mergers are thereby less likely (Fang et al., 2014); conversely, a reduction in liquidity may have a negative effect on innovation if the ability to raise future capital is lower (Brown et al., 2009, 2013). Third, firms with pronounced end-of-day dislocation and information leakage may be less likely to be the subject of mergers, which, in turn, reduces the possibility of takeovers and, hence, reduces the likelihood of employee layoffs, thereby increasing the incentives of employees to innovate (Fang et al., 2014). While these and possible other second-order effects may exist in practice, they are not expected to dominate the first-order effects summarized above.

We test the two hypotheses summarized above and listed in Table 2.1, below.

2.3. Data and Variable Construction

2.3.1 Sample Selection and Data Sources

This study covers 11 stock exchanges from nine countries from 2003 to 2010. The sample includes Australia (the Australian Securities Exchange [ASX]), Canada (the TSX Venture Exchange [TSXV]), China (the Shanghai Stock Exchange [SSE]), India (the Bombay Stock Exchange [BSE] and the National Stock Exchange of India Ltd. [NSE]), Japan (the Tokyo Stock Exchange [TSE]), New Zealand (the New Zealand Stock Exchange [NZX]), Singapore (the Singapore Exchange Ltd. [SGX]), Sweden (the Stockholm Stock Exchange [STO]) and the United States (the Nasdaq Stock Market [NASDAQ] and the New York Stock Exchange [NYSE]). Table 2.2 provides the definition and source of variables used in the study.

[Table 2.2 here]

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

*2.3.2 Mea*suring Innovation

In the study, we used two measures of patenting activity: 1) the number of patent applications made by a firm in a year, and 2) the number of citations received by these patents. The number of patent applications is a measure of the quantity or productivity of innovation, while the number of citations received is a measure of the relative importance or quality of innovation. R&D expenses were not considered in addition to patenting as a measure of innovation because of the lack of quality R&D data for international companies.

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

The second measure of innovation, INNOV_CITE(t+1), is the natural logarithm of one plus the number of citations received for patents filed in the year t+1. The number of citations received has been adjusted for truncation bias, based on the methodology developed by Hall et al. (2001, 2005). We implemented the following procedure to adjust for the truncation bias in citations: (1) For each cohort of patents applied for between 1991 and 2002, we obtain the citation lag of the patents using 12 years of actual citation data. To illustrate, for patents applied in 1991 (Cohort 1), we measure the number of citations received in each year from 1991 (citation lag of 0) to 2002 (citation lag of 11). Similarly, for patents applied for in 2002 (Cohort 12), we measure the number of citations received in each year from 2002 (citation lag of 0) to 2013 (citation lag of 11). (2) For each major IPC technology classification of patents, k, in each of the cohorts, we obtain the citation lag distribution, W, as the proportion of citations received with lags of 0 to 11 years with the total number of citations received. Subsequently, we compute the cumulative share of citations received with lags of 0 to 11 within each technology classification of patents. We average the cumulative share of citations across the 12 cohorts. (3) Finally, for patent citations received between 2003 and 2010, we divide the actual citations received by the average cumulative share of citations and use the formula:

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

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

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

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

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

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

2.3.3 Measuring Manipulation

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

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

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

2.3.4 Measuring Control Variables

The main control variables used in the study were obtained from Datastream. The control variables are measured at the end of the fiscal year t. We control for the profitability of the firm using the return on assets, ROA(t), measured as the income before extraordinary items divided by the book value of total assets. Asset tangibility, PPETA(t), is measured as the property, plant, and equipment expenditure divided by the book value of total assets. Leverage, LEV(t), is measured as the book value of debt divided by the book value of total assets. Investment in fixed assets, CAPEXTA(t), is measured as capital expenditures scaled by the book value of total assets. Firm age, LN_FIRM_AGE(t), is measured as a natural logarithm of one plus the firm i's age, approximated by the number of years listed on Datastream. Manipulation's negative effect on innovation might be stronger for smaller firms because innovators may be more aware of stock price manipulation, and hence may be more likely to change their behavior as a result. To account for this factor, we have included a MV_Decile variable within all the regression specification. The MV_Decile variable is a Market Value decile variable that takes a value of 1 to 10, based on the market value decile to which the firm belongs, within each country-year grouping, at the end of year t.

Liquidity of the firm, Liquidity(t), is computed as the natural logarithm of the inverse of the AMIHUD measure of illiquidity. AMIHUD is computed as follows:

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

where A_{iy} is the AMIHUD measure of firm i in year y. R_{it} and $Dvol_{it}$ are the daily return and daily dollar trading volume for stock i on day t. D_{iy} is the number of days with available ratio in year y.

A higher AMIHUD value indicates a higher level of illiquidity. Hence, we use the logarithm of the inverse of AMIHUD as the measure of liquidity. We have considered other variables such as price informativeness (Ding, 2015; Mathers et al., 2017) and other law and finance variables pertaining to creditor rights (La Porta et al., 1998), among other things, but did not find any material differences in the results reported herein. Other specifications are available on request.

The summary statistics of the main variables used in the study are provided in Table 2.3.

[Table 2.3 here]

2.4. Univariate Tests

Table 2.4 presents univariate comparison of means tests and shows the comparison of the percentage change in patent applications [patent citations] for firms that experienced manipulation versus those that have not experienced end-of-day dislocation or information leakage over the period from t-1 to t+1, where t is the year in which there was manipulation. The non-manipulation sample in Table 2.4 is any firm-year observation where the EOD dummy or the information leakage dummy is equal to zero. Panel A shows the results for patent application. Panel B shows the results for patent citations. We separate the tests into regimes with high versus low intellectual property rights (where 5 is the cutoff, to account for very weak legal environments).

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

[Table 2.4 here]

Table 2.4 also presents the univariate comparison tests for firms that have and have not experienced information leakage events. The data indicate that firms in low IPR environments that have experienced information leakage have a greater percentage increase, at 8.65%, in patent applications than those that have not, at 2.99%, and these differences are significant at the 1% level, consistent with Hypothesis 2; however, there is not a significant difference in patent citations among these firms in low IPR environments. Firms in high IPR environments that have experienced information leakage have a greater percentage increase, at 4.25% [21.89%], in patent applications [patent citations] than those that have not, at 0.43% [6.18%], and these differences are significant at the 1% level.

Overall, the univariate tests are consistent with Hypothesis 1, that the impact of dislocation on patents is strongly negative and statistically significant, and this effect is particularly strong in low IPR regimes. However, the impact of information leakage on patents is strongly positive and significant, consistent with Hypothesis 2, and this effect is significant in both low and high IPR regimes. These effects are depicted graphically in Figures 2.1, 2.2.A and 2.2.B.

[Figures 2.1 and 2.2 here]

To complement the univariate statistics, in Figure 2.1.A we present end-of-day dislocation and percentage changes in subsequent year patent applications by industry sector. The data indicate that for 8 of 11 sectors (not including oil and gas, banks, and software and computer services), there were higher levels of innovation among non-end-of-day dislocation firms. These differences were statistically significant for technology hardware and equipment, mining, industrial engineering, pharmaceuticals and biotechnology (consistent with other work linking capital markets to market intelligence such as Markovitch, Steckel and Young, 2005), and software and computer services, at the 10% level, and insignificant in the other industries. Overall, the evidence in Figure 2.3.A strongly supports Hypothesis 1.

[Figures 2.3.A and 2.3.B here]

Figure 2.3.B presents information leakage and percentage changes in subsequent year patent applications by sector. The data indicate that innovation was higher in every sector in the year after information leakage except for in the area of financial services, and the differences were statistically significant for mining (1%), chemicals (5%), technology hardware and equipment (5%), and electronic and electrical equipment (10%). Overall, the evidence in Figure 2.3.B strongly supports Hypothesis 2.

2.5. Multivariate Tests

2.5.1. Base Model Specifications

Tables 2.5 and 2.6 present the baseline regression estimates with pooled OLS and random effects, respectively.[3] We use the following regression specification in the case of pooled OLS method:

$$\begin{aligned}\mathrm{INNOV\_PAT(i,t+1)}\ [\mathrm{INNOV\_CITE(i,t+1)}] \\ &= \mathrm{a} + \mathrm{b1} * \mathrm{EOD\_Dummy\_First(i,t)} + \mathrm{b2} * \mathrm{EOD\_Dummy\_Subsequent(i,t)} + \mathrm{c} \\ &\quad * \mathrm{Infoleak\_Dummy(i,t)} + \mathrm{c'Controls} + \mathrm{YR(t)} + \mathrm{Firm(i)} + \mathrm{error(i,t)}\end{aligned}$$

The following regression specification is used in the case of Random effects model:

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

$$\begin{aligned}\mathrm{INNOV\_PAT}(i,t+1)\ [\mathrm{INNOV\_CITE}(i,t+1)]\\ = a + b1*\mathrm{EOD\_Dummy\_First}(i,t) + b2*\mathrm{EOD\_Dummy\_Subsequent}(i,t) + c\\ *\mathrm{Infoleak\_Dummy}(i,t) + c1'\mathrm{Country\_variable}(\mathrm{Enforcement\ and\ IPR})\\ + c2'\mathrm{Interaction\_Country\_variable\_EOD} + c3*\mathrm{Interaction\_Liquidity\_EOD}\\ + d'\mathrm{Controls} + \mathrm{YR}(t) + \mathrm{Sector}(i) + \mathrm{error}(i,t)\end{aligned}$$

Table 2.6 differs from Table 2.5 in that the use of random effects enables the inclusion of country-level institutional indices that do not vary over time. The results from the three regression models in Table 2.5 and five regression models in Table 2.6 are quite consistent and not sensitive to the inclusions of different sets of right-hand-side variables.

[Tables 2.5 and 2.6 here]

Tables 2.5 and 2.6 indicate that the end-of-day dummy variable for the first year, in which there was dislocation, is statistically insignificant in all of the specifications, but the end-of-day subsequent dummy variable is negative and significant at least at the 5% level of significance in all of the specifications, consistent with Hypothesis 1. The economic significance is such that firms that have experienced end-of-day dislocation have lower patents by 3.5% in the most conservative estimate (Table 2.6, Panel A, Model 3), and by 7.7% in the least conservative estimate (Table 2.6, Panel A, Model 4).

The dependent variable in these studies are certainly over dispersed with even the 75th percentile of patent equal to zero. To ensure our results are robust, we have also tried using a zero-inflated negative binomial model and found that our results were consistent in this specification as well. A zero-inflated negative binomial model is well suited to model data where the dependent variable has a lot of zero values.

In the above analyses, we have only considered the innovation output as measured by patent applications. This may raise the question that the negative effect of EOD manipulation on innovation may be a result of overinvestment. If this were the case, our results should not hold if we were considering only radically new and high-quality patents. While not a perfect measure of patent quality, citations do provide some insight into how important a patent is. Manipulation not just has a negative effect on total innovative output, as measured by patent applications, but we also observe a reduction in quality patents as well. This indicates that the reduction in innovation is not necessarily just associated with a fix to an overinvestment issue. Similarly, following end-of-day dislocation, firms lower their citations by 15.4% in the most conservative estimate (Table 2.6, Panel B, Model 5) and by 25.1% in the least conservative estimate (Table 2.6, Panel B, Model 1). As an alternative specification, in which we use a count of the number of dislocation cases (Table 2.5, Model 2 and Table 2.6, Model 2), we see that a 1-standard deviation increase in the number of dislocation cases is associated with a 1.5% reduction in the number of patents in the most conservative estimate (Table 2.5, Panel A, Model 2) and a 1.9% reduction in the number of patents in the least conservative estimate (Table 2.6, Panel A, Model 2). Similarly, a 1-standard deviation increase in the number of dislocation cases is associated with a 5.9% reduction (Table 2.5, Panel B, Model 2) in the number of citations in the least conservative estimate and a 6.4% reduction in the number of citations in the least conservative estimate (Table 2.6, Panel B, Model 2)

A 1-standard deviation increase in liquidity is associated with a 46% increase in the number of patents and a 78.6% increase in the number of citations in the subsequent period (Table 2.6, Model 1 and Models 2-5 are very similar). This finding is in contrast to the Fang et al. (2014) results in the U.S., but that study was based on a U.S.-only sample from an earlier time period, 1994-2005, while our sample is based on nine countries from 2003 to 2010. In Appendix A, we study the U.S.-only sample from 2003 to 2005 and the same data as Feng et al. (2014) and find results consistent with Tables 4 and 5 with a positive effect of liquidity on innovation. Also, these results indicate that the relation between liquidity and patenting is perhaps not completely stable over time. Also, Fang at al. do not examine whether or not a stock was manipulated, such as through insider trading or end-of-day manipulation. Appendix B performs further robustness tests of the relation between liquidity and innovation with propensity score matched analyses, and shows a consistent and positive effect of liquidity on innovation for 3 out of four tests: nearest-neighbor matching for the change in the number of patents, four-nearest-neighbor matching for the change in the number of patents, and four-nearest-neighbor matching for the change in the natural log of the number of patents; the nearest-neighbor matching for the change in the number of patents without logs shows a positive but statistically insignificant effect of liquidity on patents.

Further, Table 2.6, Panel A (Panel B), Model 5 shows that the interaction between liquidity and end-of-day dislocation is statistically significant at the 1% level, and the positive association between liquidity and the number of patents (number of citations) is less pronounced by 8.7% (26.4%) for firms that have experienced end-of-day dislocation. These new findings in Tables 4 and 5 indicate that the positive effect of liquidity on innovation is mitigated by the presence of end-of-day dislocation. Overall, the data indicate that the relation between liquidity and innovation may be more nuanced by other market microstructure factors, and the changes in microstructure factors over time could account for at least part of the changes in the relation between liquidity and innovation over time.

Some of the other control variables in Tables 4 and 5 are significant in ways that we might expect. Most notably, a 1-standard deviation increase in the IPR index is associated with a 47.8%

increase in the number of patents (Table 2.6, Panel A, Models 4 and 5) and a 66% increase in the number of citations in the subsequent period (Table 2.6, Panel B, Models 4 and 5), which is consistent with a large amount of literature documenting the importance of IPR in spurring innovation (e.g., Branstetter et al., 2006; Blind, 2012). As a related matter, at the country level, a 1-standard deviation increase in the Enforcement Index (La Porta et al., 1998) is associated with a 56.1% increase in the number of patents (Table 2.6, Panel A, Model 3) and a 50.5% increase in the number of citations in the subsequent period (Table 2.6, Panel B, Model 3).

Some of the firm-specific control variables are statistically significant as well. The data indicate that a 1-standard deviation increase in ROA is associated with a 2.3% decrease in the number of patents in the subsequent period (Table 2.6, Model 1 and Models 2-5 are similar). A 1-standard deviation increase in leverage is associated with a 2.2% increase in the number of patents in the subsequent period (Table 2.6, Model 4, but this effect is insignificant in Models 1 and 2). A 1-standard deviation increase in capital expenditures over assets is associated with a 2.1% decrease in the number of patents in the subsequent period (Table 2.6, Model 1 and Models 2-5 are similar). A 1-standard deviation increase in market/book is associated with a 2.5% decrease in the number of patents in the subsequent period (Table 2.6, Model 1 and Models 2-5 are similar). And, finally, a 1-standard deviation increase in the natural logarithm of the firm's age is associated with a 47.5% increase in the number of patents in the subsequent period (Table 2.6, Model 1 and Models 2-5 are similar).

2.5.2. Robustness Checks

The remaining regression tables and appendices present further robustness checks to account for other subsamples of the data, measurement issues, endogeneity, and regression model specifications, which are as follows. To maintain conciseness, we present only the results considering the number of patents, INNOV_PAT, as the main dependent variable. Table 2.7, Panel A, Model 1 shows the results with the non-US subsample, and the data and results are consistent with the full-sample results reported in Table 2.5 and Table 2.6, with the economic significance of EOD manipulation slightly more pronounced. Model 2 excludes the global financial crisis period from August 2007 to December 2008, and the findings are consistent. Model 3 includes the global financial crisis period only, and the impact of EOD manipulation on patents is stronger (almost twice as large as the non-financial crisis period). Models 4, 5, and 6 show a negative effect of EOD manipulation on patents for the subset of applied and granted patents, including adjustments for truncation bias, and winsorizing, respectively.

The information leakage variable for suspected insider trading is negative and statistically significant in Table 2.7, Model 3 for the crisis years only, consistent with Levine et al. (2015) that insider trading is a detriment to innovation. But these results are not stable for information leakage in Models 4 and 5 in Table 2.7, Panel A, which shows a positive and significant effect for applied and granted patents, and applied and granted patents adjusted for truncation bias, consistent with Hypothesis 2. These results imply that insiders have a pronounced incentive to encourage innovation if they can engage in insider trading and reap exacerbated benefits from such innovation. In particular, we find that the economic significance is such that the presence of information leakage increases a subsequent year's patent citation from 5.1% (Table 2.5, Panel B, Model 2) to 6.4% (Table 2.5, Panel B, Model 1). Also, the economic significance is such that the presence of leakage cases increases a subsequent year's patent citation by 5.1%. Estimated differently, a 1-standard deviation increase in the number of information leakage cases in one year is associated with a 1.65 % increase in patent citations in the subsequent year (Table 2.5, Panel B, Model 2). This effect is slightly different in magnitude in Table 2.6, Panel B for patents that have been applied for and granted and adjusted for truncation bias; the presence of information leakage increases a subsequent year's patents from 5.16% (Model 1) to 5.19% (Model 2). Table 2.6, Panel B, Model 3 shows that the economic significance is such that the presence of information leakage increases a subsequent year's patents applied for and granted by 6.51%.

Table 2.7, Panel B shows robustness to different patent measures (adjusted applied and granted in Models 1 and 2, and applied and granted in Model 3), and citations per patent (Model 4). Table 2.7, Panel C shows stability of the negative effect of EOD manipulation on patenting for different types of clustering (Petersen, 2009) and by industry-year and country-year in Models 1 and 2, respectively. Models 3 and 4 show similar stability of this main result with different winsorizing at 2.5%/97.5%, and 5%/95%, respectively.

The other control variables in Table 2.7, Panels A, B and C are statistically significant in ways that are consistent with the results in Tables 2.5 and 2.6. Liquidity and the Intellectual Property Rights Index are positively and significantly related to liquidity at the 1% level in all of Models 1-6. Likewise, the other firm-specific variables are consistent with the findings reported earlier.

[Table 2.7 here]

We also checked whether the direction of End of Day price manipulation had any effect on the subsequent effect on innovation (results not tabulated). We did not find any divergence in the effects, with both positive as well as negative EOD manipulations resulting in negative innovation outcomes in the following year. We believe that this is because in both cases, negative and positive EOD manipulation, firms have incentives to reduce innovative activity. In the case of negative EOD manipulation, the negative effect on equity valuations would reduce the incentives of employees with stock options and encourage the management to engage in more short term projects with immediate payoffs. Whereas, in the case of positive EOD manipulation, we believe the management also has reduced incentives to innovate because they need to focus on short term projects with immediate payoffs in order to maintain the overvalued equity. In summary, any type of mis-valuation of equity, whether positive or negative, has a subsequent negative effect on innovation.

It is possible for a firm to have experienced both EOD manipulation as well as Information leakage in a given year. We removed observations where a firm experienced both information leakage and EOD manipulation, and performed the baseline regression (results not tabulated). Our results were robust to the exclusion of these observation.

Table 2.8 shows the results for different liquidity deciles. The data indicate that EOD manipulation has a strong, statistically significant negative effect on innovation in Models 1 and 2 for the top 10^{th} and 20^{th} liquidity deciles, but not the bottom 80^{th} and 90^{th} deciles in Models 3 and 4, respectively. The other control variables, including liquidity, are significant in ways indicated above for Models 1 and 2. However, in Models 3 and 4, the other control variables are largely insignificant, except for the IPR index and Liquidity in Model 3.

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

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

[Table 2.8 here]

Table 2.9 shows the results for the days on which EOD dislocation is more likely to be associated with manipulation, namely the end-of-the-month days, where manipulators have a pronounced incentive to push up the price for reasons of compensation and option expiration. The data indicate that the effect of EOD manipulation is stronger when end-of-month days are considered. Also, the data shows that the impact of EOD manipulation is statistically significant regardless of whether or not the other manipulation days are included in or excluded from the sample.

[Table 2.9 here]

Table 2.10 reports the results with propensity score matching. The first step regressions show factors that are connected to more frequent EOD manipulation and information leakage. Note that the two alternative specifications with and without the liquidity variable affect the sign and significance of lagged patenting on EOD manipulation and information leakage. As mentioned in the introduction, on average, firms with more innovation are more likely to be associated with manipulation, and, similarly, firms with higher liquidity have more innovation (see Appendix A). The alternative first-stage specifications, however, do not affect the second-stage regressions. In the second step regressions, the data show a consistent and negative effect of EOD manipulation on innovation for four out of four tests in Models 1 and 2: nearest-neighbor matching for the change in the number of patents (with and without logs), and four-nearest-neighbor matching for the change in the number of patents (with and without logs). For the information leakage results in Table 2.10, the effect is insignificant for the change in the number of patents in Model 3, but negative and significant for the change in the natural log of the number of patents in Model 4.

[Table 2.10 here]

Also, we considered 2SLS tests of the impact of EOD manipulation and information leakage on innovation. One instrument we had used was the lagged patents in the industry, with the intuition that some industries may be subjected to different levels of manipulation. Another instrument we had used was lagged manipulation at the industry level, with the intuition that firms in some industries consistently experience more manipulation over time. We recognize that neither of these instruments is ideal, as they don't perfectly satisfy the exclusion restriction. Nevertheless, the statistical and economic significance of the second-stage results for the effect of EOD patents are not materially affected by the specification of the first-stage model. The economic significance in the second-stage estimate for EOD manipulation on patents is stronger with the use of different instruments than without. Alternative specifications not presented here but are available on request.

Due to the lack of a good instrument, we rely on propensity score matching analysis to mitigate the endogeneity issue. We find that in fact, before the manipulation event - the firms that did get manipulated had a much higher level of innovation than those that didn't get manipulated. So a highly innovative firm is in fact more likely to get manipulated, and we believe that any endogeneity present is likely to act against us finding any results.

2.6. Limitations and Extensions

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

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

2.7. Conclusion

This paper studied the impact of suspected market manipulation, including end-of-day manipulation and insider trading around information leakage events, on the number of patents and the number of citations, based on a sample of nine countries spanning the years 2003-2010. The data indicate that end-of-day dislocation mitigates the number of patents and the number of citations received by patents due to the associated short-termism of the firm's orientation, the long-term harm to a firm's equity values, and commensurate reduced incentives for employees to innovate. Our findings are robust to numerous robustness checks on subsamples of the data, propensity score matching analyses, difference-in-differences tests for firms with and without dislocation, among other factors.

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

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

Table 2.1. Connecting Market Microstructure to Innovation

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

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

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

Table 2.2. Variable Definitions

Variable	Definition	Data source
INNOV_PAT(t+1)	Natural logarithm of one plus firm *i*'s total number of patents filed in year *t*+1.	PATSTAT
INNOV_CITE(t+1)	Natural logarithm of one plus firm *i*'s total number of citations received for patents filed in year *t*+1. The number of citations has been adjusted for truncation bias using the citation lag distribution.	PATSTAT
INNOV_PAT_GRNT(t+1)	Natural logarithm of one plus firm *i*'s total number of patents filed and eventually granted in the year t+1	PATSTAT
INNOV_PAT_GRNT_ADJ(t+1)	Natural logarithm of one plus firm *i*'s total number of patents filed and eventually granted in the year t+1, which has been adjusted for truncation bias using the grant lag distribution.	PATSTAT
Average_industry-year_patents(t-1)	The average INNOV_PAT(t-1) for an industry within each country, in the year t.	PATSTAT
CHANGE_NUM_PAT	Change in the number of patents computed as firm *i's* total number of patents filed in the year t+1 minus firm *i's* total number of patents filed in the year t-1	PATSTAT
CHANGE_LN_PAT	Natural logarithm one plus firm *i's* total number of patents filed in the year t+1 minus the natural logarithm of one plus firm *i's* total number of patents filed in the year t-1.	PATSTAT
EOD_Dummy	Indicates if a firm i has experienced end-of-day (EOD) dislocation in year t CMCRC and SMARTS surveillance staff constructed the dislocation of EOD price case by looking at the price change between the last trade price (P_t) and the last available trade price 15 minutes before the continuous trading period ends (P_{t-15}). For securities exchanges that have a closing auction, the close price at auction is used ($P_{auction}$). A price movement is dislocated if it is four standard deviations away from the mean price change during the benchmarking period for the past 100 trading days. To be considered as a dislocation of EOD price case, at least 50% of the price dislocation has to revert at open on the next trading day. Hence, the price movement between the last trade price (P_t) and the next day opening price (P_{t+1}), and between the last trade price (P_t) and	CMCRC

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

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

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

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

Table 2.3. Summary Statistics

Table 2.3 reports the summary statistics for variables constructed using a sample of public firms from Australia, Canada, China, India, Japan, New Zealand, Singapore, Sweden, and the United States. The Innovation variables are measured from 2004 to 2011. The EOD / Infoleak variables and the control variables are measured from 2003 to 2010.

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

Table 2.4. Comparison of the Percentage of Change in the Number of Patent Applications

Table 2.4 compares the percentage of change in the number of patents between t-1 and t+1, for both firms that have experienced end-of-day price manipulation (information leakage) and those that have not experienced end-of day-price manipulation (information leakage). The sample has been split into High IPR and Low IPR, where High IPR are observations with an IPR index value over 5 and Low IPR are observations with an IPR index value less than 5. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

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

Table 2.5. Pooled OLS Specification

Table 2.5, Panel A [B] reports Pooled OLS regression results of the model INNOV_PAT(i,t+1) [INNOV_CITE(i,t+1)] = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c'Controls + YR(t) + Firm(i) + error(i,t). INNOV_PAT(i,t+1) is the natural logarithm of one plus firm i's total number of patents filed in year t+1. INNOV_CITE(i,t+1) is the natural logarithm of one plus firm i's total number of citations received for patents filed in year t+1, which has been adjusted for truncation bias using the citation lag distribution. EOD_Dummy_First [EOD_Dummy_Subsequent] indicates if firm i has experienced end-of-day (EOD) dislocation in year t, under the condition that firm i never previously experienced [has previously experienced] EOD dislocation. Infoleak_Dummy indicates if firm i has experienced information leakage in year t. Similarly, Num_EOD_Cases_First, Num_EOD_Cases_Subsequent and Num_Infoleak_cases measure the number of times firm i has experienced EOD or Information leakage in year t. EOD_Dummy_Positive(t) indicates if firm i has experienced more positive EOD price dislocations than negative price dislocations in year t. Liquidity(t) is the natural logarithm of the inverse of the AMIHUD illiquidity variable. Interaction_Liquidity_EOD(t) mixes Liquidity(t) and EOD_Dummy_Subsequent variables. Intellectual Property Rights Index, IPR_Index(t), is the Intellectual Property Rights Index obtained from the International Property Rights Index Report. Market value decile is (MV_Decile(t)), to which firm i belongs within each country-year; Return on Assets is (ROA(t)); Property plant and equity to total assets is (PPTA(t)); leverage measured as the book value of debt to book value of assets is (LEV(t)); Capital expenditure to total assets is (CAPEXTA(t)); Tobin's Q is (Q(t)); and natural logarithm of one plus firm i's age, approximated by the number of years listed on Datastream is (LN_Firm_Age(t)), used as controls in all the models. No time invariant variables or interactions of time invariant variables are included in this model. Year fixed effects YR(i) and firm fixed effects Firm(i) are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

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

	(1)		(2)		(3)		(4)	
EOD_Dummy(t)	-0.00803	**						
EOD_Dummy_First(t)			0.00380		-		0.00365	
EOD_Dummy_Subsequent(t)			-0.01742	***	-		-0.01328	***
EOD_Dummy_Positive(t)			-0.00120		-0.00368		-0.00145	
Infoleak_dummy(t)	-0.00640		-0.00622		-		-0.00624	
Num_EOD_Cases_First(t)			-		0.00061		-	
Num_EOD_Cases_Subsequent(t)			-		-0.00122	***	-	
Num_Infoleak_cases(t)			-		-0.00372		-	
Liquidity(t)	0.01235	***	0.08598	***	0.08624	***	0.01266	***
Interaction_Liquidity_EOD (t)			-		-		-0.00267	**
IPR_index(t)	0.08491	***	0.01228	***	0.01218	***	0.08594	***
MV_Decile(t)	0.00246	*	0.00258	*	0.00259	*	0.00256	*
ROA(t)	-0.00468		-0.00483		-0.00482		-0.00498	
PPETA(t)	0.00530		0.00547		0.00535		0.00537	
LEV(t)	0.02556	**	0.02618	**	0.02599	**	0.02637	**

CAPEXTA(t)	-0.03452	**	-0.03519	**	-0.03475	**	-0.03553	**
Q(t)	-0.00132	*	-0.00135	*	-0.00134	*	-0.00136	*
Year and Firm fixed effects	Included		Included		Included		Included	
Sector fixed effects	Included		Included		Included		Included	
Number of observations used	97148		97,148		97,148		97148	
Adjusted R2	0.9106		0.9106		0.9106		0.9106	

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

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

Table 2.6. Random Effects Specification

Table 2.6, Panel A [B] reports Firm Random Effects regression results of the model INNOV_PAT(i,t+1) [INNOV_CITE(i,t+1)] = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c1'Country_variable(Enforcement and IPR) + c2'Interaction_Country_variable_EOD + c3*Interaction_Liquidity_EOD + d'Controls + YR(t) + Sector(i) + error(i,t). INNOV_PAT(i,t+1) is the natural logarithm of one plus firm i's total number of patents filed in year t+1. INNOV_CITE(i,t+1) is the natural logarithm of one plus firm i's total number of citations received for patents filed in year t+1, which has been adjusted for truncation bias using the citation lag distribution. EOD_Dummy_First [EOD_Dummy_Subsequent] indicates if firm i has experienced end-of-day (EOD) dislocation in year t, under the condition that firm i never previously experienced [has previously experienced] EOD dislocation. Infoleak_Dummy indicates if firm i has experienced information leakage in year t. Similarly, Num_EOD_Cases_First, Num_EOD_Cases_Subsequent and Num_Infoleak_cases measure the number of times firm i has experienced EOD or Information leakage in year t. EOD_Dummy_Positive(t) indicates if firm i has experienced more positive EOD price dislocations than negative price dislocations in year t. Liquidity(t) is the natural logarithm of the inverse of the AMIHUD illiquidity variable. The Enforcement_index is formed by adding the rule of law, efficiency of judiciary, risk of expropriation, repudiation of contracts by government, and corruption variables provided by LLSV, and scaling the index to be between 0 and 1 (1998). The Intellectual Property Rights index, IPR_Index, is obtained from the International Property Rights Index report. Interaction_Liquidity_EOD, Interaction_Enforcement_EOD, and Interaction_IPR_EOD mixes the Liquidity(t), Enforcement_index(t) and IPR_Index(t), respectively, with the EOD_Dummy_Subsequent variable. Market value decile is (MV_Decile(t)), to which firm i belongs within each country-year; Return on Assets is (ROA(t)); Property plant and equity to total assets is (PPTA(t)); leverage measured as the book value of debt to book value of assets is (LEV(t)); Capital expenditure to total assets is (CAPEXTA(t)); Tobin's Q is (Q(t)); and the natural logarithm of one plus firm i's age, approximated by the number of years listed on Datastream is (LN_Firm_Age(t)), used as controls in all the models. Year fixed effects and industry fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

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

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

Num_Infoleak_cases(t)					-0.00212							
Liquidity(t)	0.03245	***	0.03244	***	0.03230	***	0.02548	***	0.03014	***	0.03048	***
Enforecement_index							1.39727	***				
IPR_Index									0.10116	***	0.10152	***
Interaction_Enforcement_EOD							0.03676	*				
Interaction_IPR_EOD									0.00159			
Interaction_Liquidity_EOD											-0.00266	**
MV_Decile(t)	0.00236	*	0.00246	*	0.00242	*	0.00579	***	0.00461	***		***
ROA(t)	-0.01919	***	-0.01930	***	-0.01929	***	-0.01656	***	-0.01923	***	0.00458	***
PPETA(t)	-0.00199		-0.00182		-0.00191		0.01521	*	0.00904		-0.01938	
LEV(t)	0.01463		0.01526		0.01498		0.02433	**	0.03146	***	0.00890	***
CAPEXTA(t)	-0.07966	***	-0.08043	***	-0.07995	***	-0.05881	***	-0.07135	***	0.03156	***
Q(t)	-0.00298	***	-0.00300	***	-0.00297	***	-0.00395	***	-0.00389	***	-0.07175	***
LN_Firm_Age(t)	0.28193	***	0.28267	***	0.28291	***	0.27571	***	0.26254	***	-0.00390	***
Year fixed effects	Included		Included		Included		Included		Included		Included	
Industry fixed effects	Included		Included		Included		Included		Included		Included	
Number of observations used	97,148		97,148		97,148		90,272		97,148		97,148	
R2	0.2310		0.2314		0.2310		0.2550		0.2543		0.2541	

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

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

Enforecement_index							1.44248	***				
IPR_Index		***							0.16000	***	0.15408	***
Interaction_Enforcement_EOD							-0.22679	***				
Interaction_IPR_EOD									-0.03288	***		
Interaction_Liquidity_EOD											-0.01676	***
MV_Decile(t)	0.01612	***	0.01654	***	0.01632	***	0.02055	***	0.01768	***	0.01881	***
ROA(t)	-0.07764		-0.07782	***	-0.07787	***	-0.06956	***	-0.06673	***	-0.06829	***
PPETA(t)	-0.00089	*	-0.00010		-0.00025		0.03112		0.03267	*	0.03136	
LEV(t)	-0.04747	***	-0.04453	*	-0.04585	*	0.00319		0.00656		0.00769	
CAPEXTA(t)	-0.25134	***	-0.25371	***	-0.25237	***	-0.20404	***	-0.22188	***	-0.21957	***
Q(t)	-0.00745	***	-0.00753	***	-0.00746	***	-0.00915	***	-0.00811	***	-0.00817	***
LN_Firm_Age(t)	0.26087	***	0.26412	***	0.26421	***	0.23686	***	0.22725	***	0.22608	***
Year fixed effects	Included		Included		Included		Included		Included		Included	
Industry fixed effects	Included		Included		Included		Included		Included		Included	
Number of observations used	97148		97,148		97,148		90,272		97,148		97,148	
R2	0.2005		0.2309		0.2305		0.2750		0.2687		0.2534	

Table 2.7. Robustness Checks

Table 2.7 reports various robustness check regression results of the Firm Random Effects model INNOV_PAT(i,t+1) = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c1'IPR_Index + d1*Liquidity + d2*Interaction_Liquidity_EOD + e'Controls + YR(t) + Industry(i) + error(i,t). Year fixed effects YR(i) and Industry(i) fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

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

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

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

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

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

CAPEXTA(t)	-0.07043	***	-0.09071	***	-0.02307		-0.00060	
Q(t)	-0.00354	***	-0.00520	***	-0.00610	***	0.00000	***
LN_Firm_Age(t)	0.37413	***	0.25431	***	0.24447	***	0.28811	***
Year fixed effects	Included		Included		Included		Included	
Industry fixed effects	Included		Included		Included		Included	
Number of observations used	66,195		70,752		26,396		97148	
R2	0.2935		0.2610		0.2788		0.2474	

Panel B: Robustness to Applied and Granted Measure of Innovation

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

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

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

Table 2.8. Liquidity Deciles

Table 2.8 reports the Firm Random Effects regression results of the model INNOV_PAT(i,t+1) = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c1'IPR_Index +d1*Liquidity + e'Controls + YR(t) + Industry(i) + error(i,t), for the 10th, 20th, 80^{th}, and 90th deciles of the Liquidity(t) measure. Year fixed effects YR(i) and Industry(i) fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

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

Table 2.9. Manipulation on Month End Dates

Table 2.9 reports the regression results of the Firm Random Effects model INNOV_PAT(i,t+1) = a + b1'Strong(Weak) _EOD_Dummy_First(i, t) + b2'Strong(Weak)_EOD_Dummy_Subsequent(i,t) + c1'Strong(Weak)_Infoleak_Dummy_First(i,t) + c2'Strong(Weak)_Infoleak_Dummy_Subsequent + c1'IPR_Index +d1*Liquidity + e'Controls + YR(t) + Industry(i) + error(i,t). The Strong form of EOD and Infoleak considers only EOD / Infoleak cases occurring during the last three trading days of the month. Model 1 includes all the firms in the sample and uses only strong form manipulation dummies. Model 2 excludes all firms that were weakly manipulated from the sample and uses only strong form manipulation dummies. Model 3 includes all the firms in the sample and uses both strong form and weak form manipulation dummies. Year fixed effects and industry fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

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

Table 2.10. Propensity Scoring Matching Analysis

Table 2.10, Panel A [Panel B] reports the Propensity score matching analysis using nearest and four-nearest matching methods for estimating the treatment effect of manipulation on innovation. First, the propensity scores for treatment (EOD or Infoleak manipulation) are computed using Probit regression of the model EOD_Dummy(t)/Infoleak_Dummy(t) = a + b*INNOV_PAT(t-1) + c*IPR_Index(t) + d*Enforcement_index(t) + e*Liquidity(t) + f'Controls. In Panel B, we exclude Liquidity(t) as an independent variable in this Probit regression.

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

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

Probit Regression

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

Average Treatment Effect on the Treated (ATT)

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

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

Probit Regression

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

Average Treatment Effect on the Treated (ATT)

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

Figure 2.1. Percentage of Change in Patent Applications/Citations and Manipulation

Figure 2.1 compares the percentage of change in the number of patent applications and patent citations from one period before the manipulation (t-1) to one period after the manipulation (t+1) for all the firms that have been manipulated and for those that have not experienced any end-of-day manipulation / information leakage.

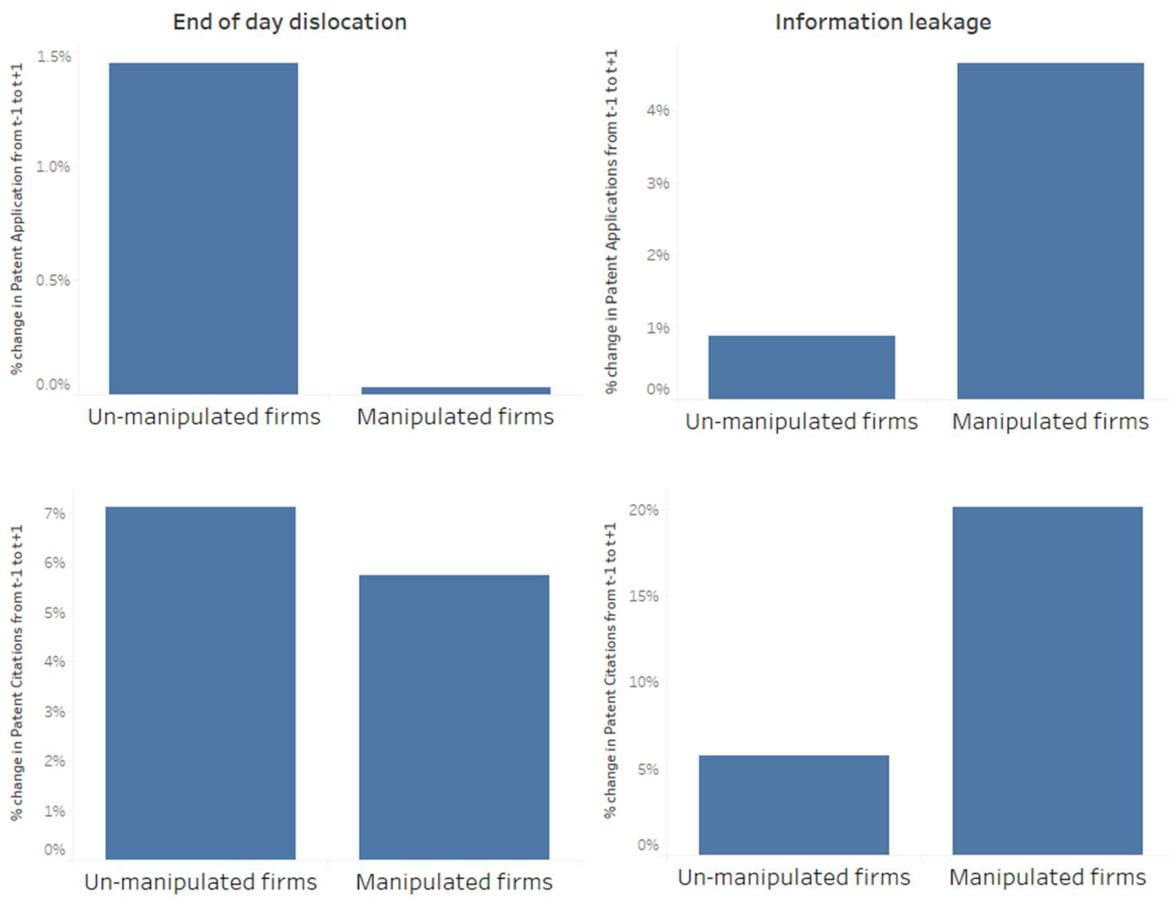


Figure 2.2.A. Percentage of Change in Patent Applications, Manipulation, and Intellectual Property Rights

Figure 2.2.A compares the percentage of change in the number of patent applications from one period before the manipulation (t-1) to one period after the manipulation (t+1) for firms that have been manipulated and for those that have not experienced any end-of-day manipulation / information leakage, after splitting the sample into firms that belong to countries with a high level of intellectual property rights (IPR) and those with a low level of IPR.

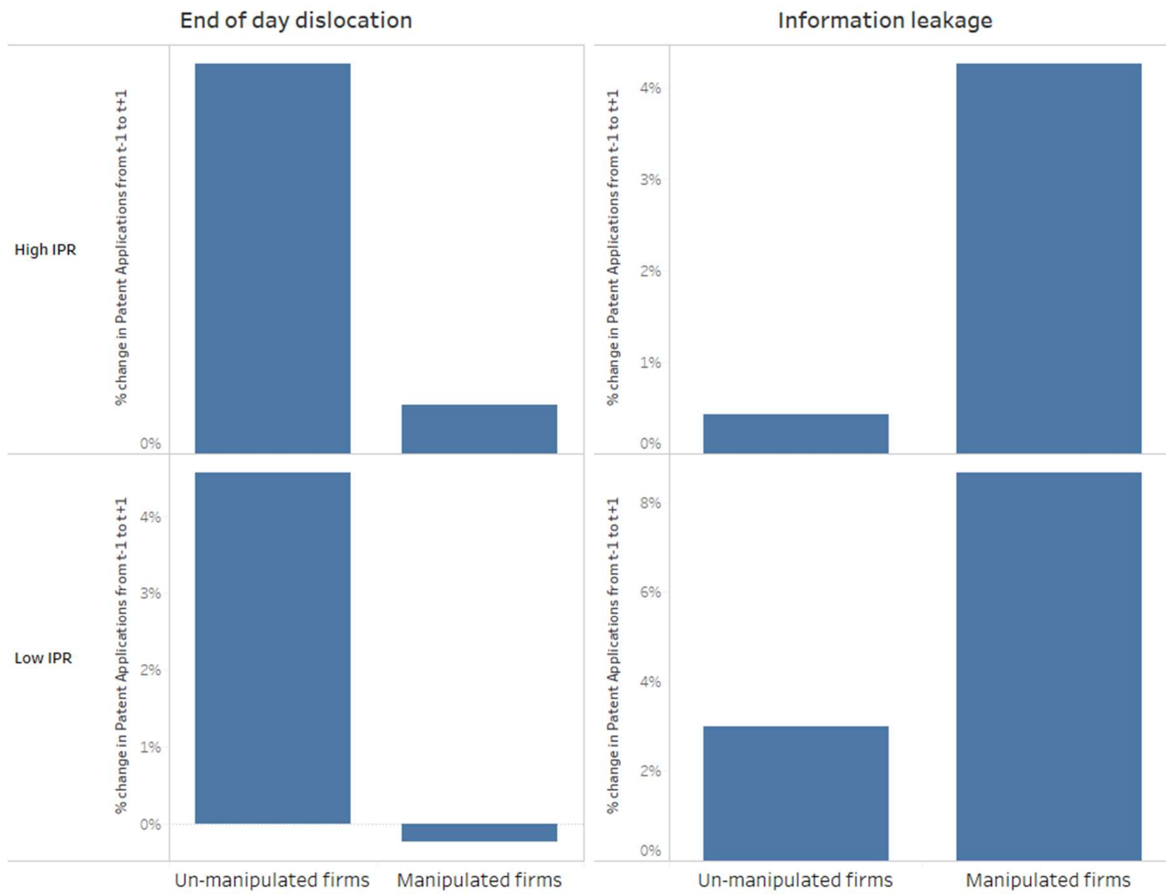


Figure 2.2.B. Percentage of Change in Patent Citations, Manipulation and Intellectual Property Rights

Figure 2.2.B compares the percentage of change in the number of patent citations from one period before the manipulation (t-1) to one period after the manipulation (t+1) for firms that have been manipulated and for those that have not experienced any end-of-day manipulation / information leakage, after splitting the sample into firms that belong to countries with a high level of intellectual property rights (IPR) and those with a low level of IPR.

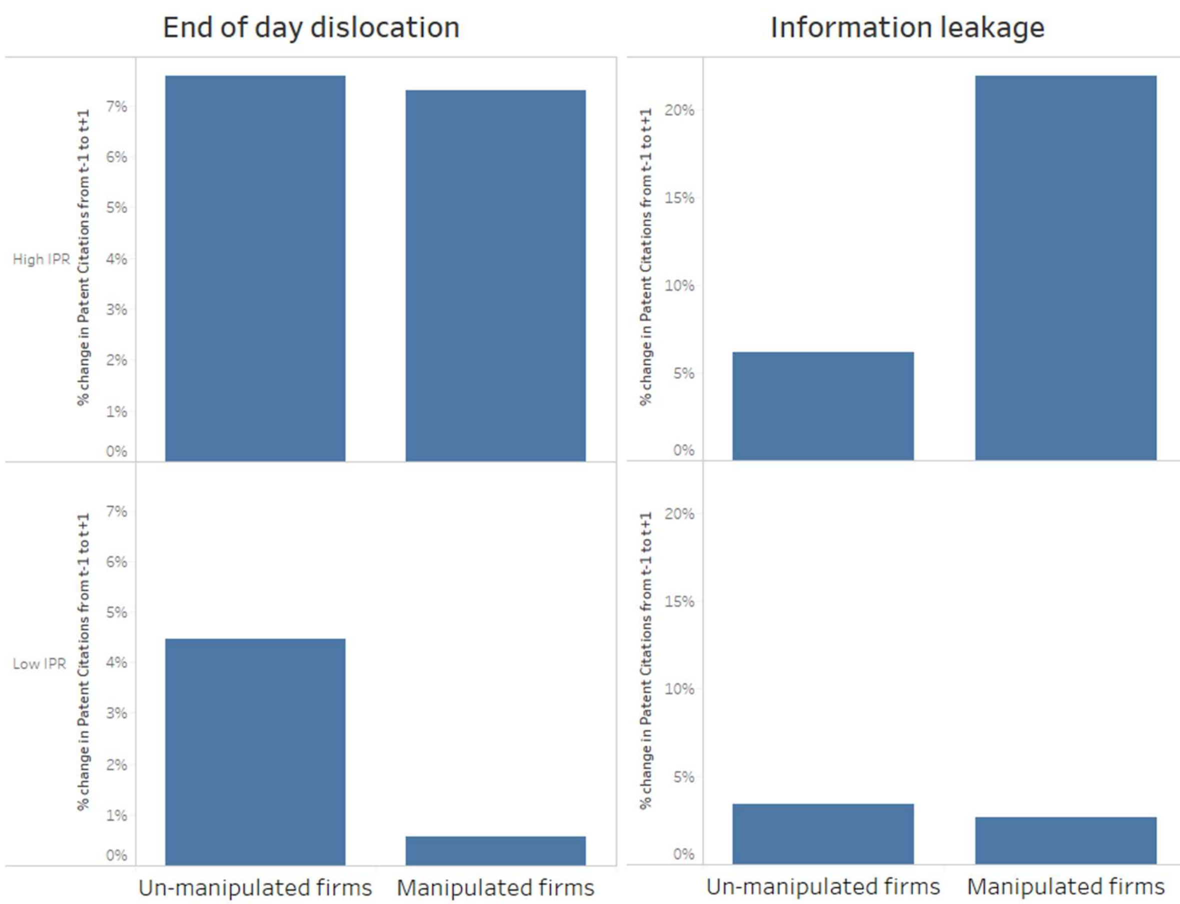
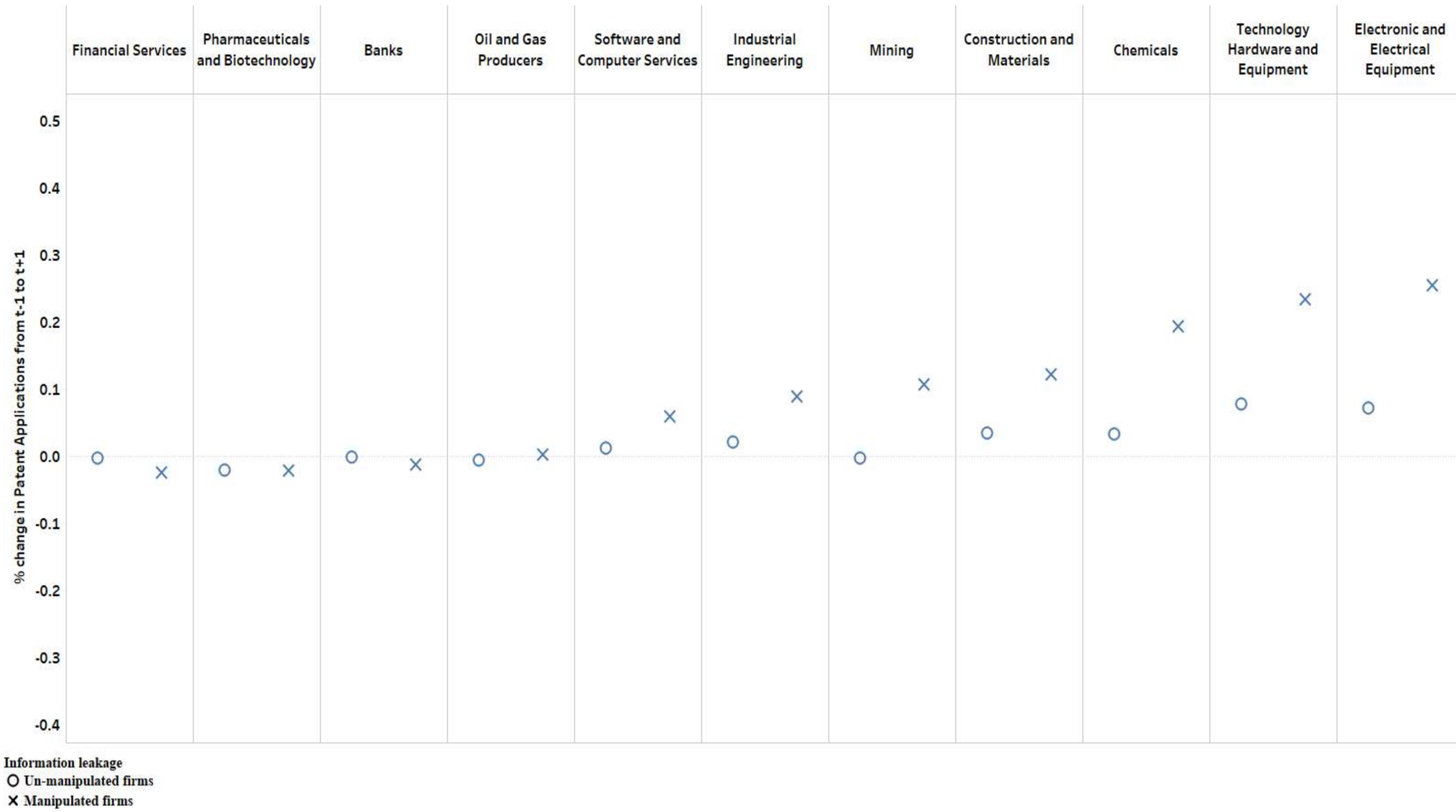


Figure 2.3.A. Percentage of Change in Patent Applications across Sectors and End-of-Day Dislocation

Figure 2.3.A compares the percentage of change in the number of patent applications from one period before the end-of-day manipulation (t-1) to one period after the manipulation (t+1) for firms that have been manipulated and for those that have not experienced any manipulation, after splitting the sample into sectors.

Figure 2.3.B. Percentage of Change in Patent Applications across Sectors and Information Leakage

Figure 2.3.B compares the percentage of change in the number of patent applications from one period before the information leakage manipulation (t-1) to one period after the manipulation (t+1) for firms that have been manipulated and for those that have not experienced any manipulation, after splitting the sample into sectors.



Appendix 2.A. Replication of Tian et al. (2014)

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

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

Appendix 2.B. Propensity Score Matching Analysis – Liquidity and Innovation

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

Panel A: Probit regression

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

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

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

ONLINE APPENDIX

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

Table 2.A.1 indicates that end-of-day manipulation negatively affects patents in all robustness checks. Information leakage negatively affects patents applied for but positively affects patents applied for and granted, suggesting that insiders take advantage of superior knowledge when then apply for a high-quality patent.

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

Table 2.A.3 shows that the results for end-of-day manipulation are robust in the subsamples including and excluding the crisis years. Table 2.A.3 also shows that the results for information leakage hold in the non-crisis period but not in the crisis period. The intuition is as follows. At any time there is the negative impact of end-of-day manipulation and information leakage on innovation due to short-termism and poor focus for both types of manipulation. For information leakage, however, there is a counter force of insiders profiting more. In bad economic times that counter force is less profitable for insiders, and the risk of being caught is greater because regulators are especially diligent in crisis periods. Consequently, the former effect of short-termism associated with information leakage is stronger than the latter effect of expected profits during crisis periods.

Table 2.A.1. Only Patenting Firms

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

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

	(1) Simple EOD Dummy		(2) EOD Dummy		(3) Number of EOD / Infoleak Cases	
EOD_Dummy(t)	-0.03751	***				
EOD_Dummy_First(t)			-0.00698			
EOD_Dummy_Subsequent(t)			-0.06540	***		
Infoleak_dummy(t)	-0.01393					
Num_EOD_Cases_First(t)					-0.00007	
Num_EOD_Cases_Subsequent(t)					-0.00480	***
Num_Infoleak_cases(t)			-0.01347		-0.00856	
Liquidity(t)	0.07656	***	0.07624	***	0.07603	***
IPR_Index	0.19115	***	0.19251	***	0.19211	***
MV_Decile(t)	0.03319	***	0.03339	***	0.03336	***
ROA(t)	-0.06583	***	-0.06592	***	-0.06584	***
PPETA(t)	0.14331	**	0.14338	**	0.14400	**

LEV(t)	0.09710	**	0.10004	**	0.09886	**
CAPEXTA(t)	-0.20342	**	-0.20872	**	-0.20686	**
Q(t)	-0.01689	***	-0.01700	***	-0.01688	***
LN_Firm_Age(t)	0.35544	***	0.35692	***	0.35760	***
Year fixed effects	Included		Included		Included	
Industry fixed effects	Included		Included		Included	
Number of observations used	30,892		30,892		30,892	
R2	0.3175		0.3173		0.3170	

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

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

Table 2.A.2. Excluding China

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

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

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

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

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

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

Table 2.A.3. Crisis Years – Patents Applied, Granted, and Adjusted

Table 2.A.3 reports Firm Random Effects regression results of the model INNOV_PAT_GRNT_ADJ(i,t+1) = a + b1*EOD_Dummy_First(i, t) + b2*EOD_Dummy_Subsequent(i,t) + c*Infoleak_Dummy(i,t) + c1'Country_variable(Enforcement and IPR) + c2'Interaction_Country_variable_EOD + c3*Interaction_Liquidity_EOD + d'Controls + YR(t) + Sector(i) + error(i,t). INNOV_PAT(i,t+1) is the natural logarithm of one plus firm i's total number of patents filed and granted, which have been adjusted for truncation bias, in year t+1. EOD_Dummy_First [EOD_Dummy_Subsequent] indicates if firm i has experienced end-of-day (EOD) dislocation in year t, under the condition that firm i never previously experienced [has previously experienced] EOD dislocation. Infoleak_Dummy indicates if firm i has experienced information leakage in year t. Liquidity(t) is the natural logarithm of the inverse of the AMIHUD illiquidity variable. The Intellectual Property Rights Index, IPR_Index, is obtained from the International Property Rights Index Report. Interaction_Liquidity_EOD mixes Liquidity(t) with the EOD_Dummy_Subsequent variable. Market value decile is (MV_Decile(t)), to which firm i belongs within each country-year; Return on Assets is (ROA(t)); Property plant and equity to total assets is (PPTA(t)); leverage measured as the book value of debt to book value of assets is (LEV(t)); Capital expenditure to total assets is (CAPEXTA(t)); Tobin's Q is (Q(t)); and natural logarithm of one plus firm i's age, approximated by the number of years listed on Datastream is (LN_Firm_Age(t)), used as controls in all the models. Year fixed effects and industry fixed effects are included in all the regressions. Coefficient estimates are shown. The standard errors are clustered by firm. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

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

Chapter 3

Buyouts and innovation

"We must help companies acting in the interest of their future and the future of their employees against irresponsible locust swarms, who measure success in quarterly intervals, suck off substance and let companies die once they have eaten them bare..."
Franz Müntefering (November 2004) [4]

3.1. Introduction

In the global economy we have been observing a shift in the ownership structure. A significant proportion of firms are now owned by institutional investors from private equity (PE) industry. In principle, the existing theories suggest, that post buyout transactions, the target firms should improve in terms of operating performance, investment, and productivity (Jensen, 1989). The early evidence suggested that the impact of private equity leveraged buyouts (LBOs) and management buyouts (MBOs) showed positive effects on productivity based on plant level data (Lichtenberg and Siegel, 1990). There was also some evidence of improved operating performance during the first buyout wave (Kaplan, 1989; Baker and Wruck, 1989; Smith, 1990).

The famous locusts speech of Franz Müntefering has arguably inspired much additional research about the value of private equity to their investee companies. The evidence, however, is mixed. For example, subsequent evidence is consistent with the positive effect of private equity on innovation, with data from the U.S. over 1983-2007 (Lerner et al., 2011) and data from the U.K. from 1998-2005 (Ames et al., 2016). Also Davis et al., (2014) show that while buyouts lead to job loses, they bring improvements in productivity. The intuition is straightforward: private equity managers are value-added active investors that put in place

[4] https://web.archive.org/web/20050905185716/https://partei.spd.de/servlet/PB/show/1043150/221204_programmheft_1.pdf

efficient incentive mechanisms and connect appropriate suppliers and strategic partners to enhance firm productivity and performance (e.g., Ahlers et al., 2017; Ames et al., 2016; Cornelli and Karakaş, 2015; Jensen, 1989). On the other hand, critics of LBOs argue that they are transitory organizations (Kaplan, 1991) which focus on projects with short term payoff and reduce the investment in long term projects, to ensure that they can meet their debt servicing obligations (Rappaport, 1990). One example of the dark side of the private equity deals is the case of the public-to-private deal that took place in the UK. The buyout of Debenhams generated enormous profits for the private equity owners, yet it left the company with huge debt and the company plummeted in value after its IPO.[5]

However, not only individual cases but also the recent empirical evidence has left us puzzled about the real outcome of the public to private transactions. Recent literature has questioned the results of performance and productivity improvements following buyouts (Cohn et al., 2014; Weir et al., 2015; Ayash and Schütt, 2016; Ayash, B. and Rastad, 2017). There is evidence that shows private equity institutional buyouts (IBO) have had negative effects on employment and productivity (Goergen et al., 2014a,b). An IBO involves the private equity fund acquiring a controlling interest in the target firm, hiring new management and exiting the deal typically within 5 years, while a MBO involves the current management and taking a large ownership position in the company.

One may come to the preliminary conclusion that the body of prior work on the topic of private equity and innovation is sufficiently detailed to encourage one to think that the case is closed on this topic. Yet, the evidence on the effect of buyouts on target firm is mixed and seems to depend on the type of the buyout wave. This recent evidence of Goergen et al. (2017) gives rise to the first of two questions that we address in this paper. Do private equity

[5] https://www.ft.com/content/6fd92a0c-437d-11dc-a065-0000779fd2ac

institutional buyouts have a differential effect on innovation relative to other types of buyouts? The recent work of Goergen et al. (2014a,b) and the global financial crisis that began in August 2007 inspires a second question that we further examine in this paper: Has there been a differential effect of private equity on innovation at different points of time, and is the effect of buyouts on innovation stable across countries? Institutional incentives for long-term value creation versus short-term profiting may have evolved in light of the financial consequences of the financial crisis. Prior work on buyouts and innovation precedes the financial crisis, and has been focused on U.S. and U.K. data.

We examine these questions and issues by using international data for 36 countries for a period 1997 to 2011. We create a unique dataset by merging several databases including Zephyr, Orbis and PATSTAT. We propose a firm-level measure of innovation from EPO's Worldwide Patent Statistical Database (PATSTAT). So far most of the previous studies used mainly R&D expenditures or the innovations registered only in the US Patent and Trademark office, yet both measures have their limitations. Our measures of innovation are based on patents registered in a country's office. PATSTAT provides data on more than 80 million patent applications filed in over 100 patent offices around the world. Furthermore, the depth of the data offered by PATSTAT allows us to create measures like radical innovation, innovation efficiency and innovator count that have not been used in the previous studies.

We find that in general buyouts reduce investment in innovation. Our tests are based on pooled and panel regressions with fixed effects. The effect of buyouts on investment in innovation is quite sizable in terms of quantity and quality. A decline in the number of patents after the buyout transaction is between 5 to 11 % in year 2 and up to 17% in year 3 post buyout transaction. The drop in quality is mostly observed in year 3 post buyout transaction and is between 22 to 38 %.

We also find that the evidence is supported for institutional buyouts, while the results from management buyouts are inconclusive.

We find a consistent negative effect following buyout, for a sample of firms that engaged in radical innovation i.e. the more scientific innovation that cites non-patent literature. The number of radical patents falls by 14% from a year after the buyout to three years after the buyout,

Furthermore, Innovation efficiency also decreases after the buyout, with Institutional buyouts experiencing a greater decrease than Management buyouts. The decrease in innovation efficiency ranges between 17% for Institutional buyouts to 15% for Management buyouts, three years after the buyout.

When we look at deals financed only by private equity we find that the effect is aggravated in post 2006 period. It suggests that the nature of deals changed. Our evidence is international and hold even after excluding the countries that are the most engaged in innovation like Germany, UK or US.

The rest of the paper is organised as follows. Section 3.2 discusses the sample selection, measures of innovation and control variables. Section 3.3 presents our main results. Section 3.4 explores additional analysis. Section 3.5 concludes.

3.2. Data

3.2.1. Sample Construction

In order to identify the sample we collect buyout transactions from Zephyr database. We only analyse the deals where the acquirer bought 100% of the target firm. We rely on Zephyr database because it shares common identities with Orbis database. We use Orbis database to obtain data on patent publication identifiers for the target companies in the Zephyr database. We then merge Zephyr – Orbis dataset with the detailed patent data derived from EPO's Worldwide Patent Statistical Database (PATSTAT), which provides data on more than 80 million patent applications filed in over 100 patent offices around the world. It contains basic bibliographic information on patents, including the identity number of the application and granted patent, the date of the patent application, the date when the patent is granted, the track record of patent citations and inventor identification for each patent application. The PATSTAT database is published biannually and we use the 2017 edition.

In essence, PATSTAT database covers patents filed in 93 non-U.S countries and has greater coverage than the National Bureau of Economic Research (NBER) Patent and Citation database that is compiled based on the United States Patent and Trademark Office (USPTO) (Moshirian, Tian, Zhang, and Zhang, 2015). USPTO only collects the patents filed in the U.S..

In summary, using databases that share common identifiers allows us to avoid many pitfalls. Both databases Zephyr and Orbis are provided by the same supplier Bureau Van Dyck therefore it is possible to match deal information from Zephyr to firm level data and patent activity from Orbis more accurately than if one were to match Thomson One SDC or CapitalIQ to Orbis. We further match these data with PATSTAT using patent publication identifier. Also, using Orbis and PATSTAT data we can directly measure firm innovation level irrespective where the patent application was filed. In addition, Zephyr's coverage of private-firm acquisitions is better than Thomson One SDC's (Erel, Jang, and Weisbach, 2015).

We include all completed buyout transactions from 1997 to 2011 (we need six years post buyout on patents) from 36 countries. Six years of post-buyout patent data is required to construct our patent citation measures. We choose only buyout deals where the target firm had at least one successful patent applied for and granted from 3 years before the transaction and to 3 years afterwards (similar to Lerner, Sorensen, and Strömberg, 2011). Our final sample involves 1,471 deals with at least one patent granted to the target firm 3 years before to 3 years after transaction. Overall those firms were granted 53,799 patents.

3.2.2 Measuring innovation

The main measure of innovation at the firm level used in the paper is the number of citations received by patents. The number of patents applied for and granted is also used as a measure of innovation.

Patents are segregated into radical and incremental innovations similar to Griffith and Macartney (2014). If a patent has at least one citation to Non-Patent literature (NPL), we consider that patent as a radical innovation. NPL generally refers to scientific journals and therefore, patents making citations to NPL are likely to be new and radical innovation.

Three separate measures of patent citations are used in the paper. The first measure, Citation count, considers all the citations received by a patent from the grant date onwards. The second measure, Absolute citation count, consider only the citations made within the three-year period, starting from the year of grant of the patent to 3 years following the grant date. The Absolute citation measure mitigates the issue of truncation towards the end of the sample. The third measure, Relative citation, computes the citations received for patents filed and subsequently granted during the year of grant to 3 years following the grant, less the average number of citations during this period that is received by matching patents. We follow Lerner (2011) to define matching patents as the patents granted in the same year and assigned the same technology class.

Since Absolute and relative citation measures require three years forward patent data and the study require citation measures three years from the date of the buyout, we require a total of 6 years of patent data from the date of the buyout. This limits us to considering buyout transaction up to the year 2011.

In addition, we also use a measure of Innovation Efficiency in the paper, which is computed as the number of patent application that has been filed during the year and subsequently granted, divided by the number of unique innovators. Unique innovators, are individuals that are listed in the patent application. If the same person has been included in multiple patent applications, we count that person only once.

3.2.3. Control Variables

There are many factors that drive innovative activity at the country and firm level. Following the previous literature on innovation we control for several characteristics at the country and firm level. In particular, we include intellectual property protection index created by Park (2008) and the level of country's innovativeness measured by patent applications scaled by GDP.

Also, as previously suggested the financial markets development affects innovative activity (Nanda and Rhodes-Kropf 2013; Hsu, Tian, and Xu, 2014). Thus, we include equity development measures proxied by the value of shares traded scaled by GDP and two credit market development measures. CMD1 is the domestic credit to private sector that is an important indicator of possibilities to finance production, consumption, and capital formation, which in turn affect economic activity. CMD2 is the domestic credit provided by financial sector scaled by GDP that measured the banking sector depth and financial sector development in terms of size. We also include GDP growth of a country to proxy for general economic conditions.

At the firm level the vector of control variables includes firm size (SIZE), firm age (AGE), and profitability (ROA). We winsorize all variables at the 1st and 99th percentiles to eliminate the effects of outliers. We provide all definitions of variables and data sources in Appendix AII.

3.2.4. Sample Characteristics

In Table 3.1 we present summary statistics. We first present the yearly distribution in Panel A. There is a sharp increase in the number of transactions after 2005 due to the cheap access to credit that was the main source of financing for LBOs. After 2008 the number of deals dropped to a level from the late 90s that can be explained by a total standstill in deals caused by financial crisis. The number of patents increases significantly from 2000. Similar to Lerner, Sorensen, and Strömberg (2011) it might be explained by increasing volume as well as growing share of technology firms that typically innovate more.

In Panel B of Table 3.1 we show the distribution of transactions by industry. Similar to previous studies (Lerner, Sorensen, and Strömberg (2011) manufacturing industries dominate in our sample.

In Panel C of Table 3.1 we present the distribution by target's country. Most of the innovative target firms are from the US, followed by the UK, Germany and France.

In Panel D of Table 3.1 we show the distribution by deal type. Our sample comprises mostly of institutional buyouts, with around 71% of the total number of buyouts. The remaining 19% are management buyouts. We define and institutional buyout as an indicator variable equal to one if "This is an acquisition where a Private Equity firm has taken a 50% stake or more in the Target company, or is the parent of the acquirer. The acquisition often takes place through a 'new company' (newco) or an acquisition vehicle. Often the Target company's management will take a small stake (If the buy-out is for less than 100 per cent of the Target company, the deal is coded as IBO X%). Many deals described in the media as MBOs are coded on Zephyr as IBOs since the management team do not take a majority stake in the Target. There are very few occasions when Venture Capital may be inserted instead of Private Equity as the financing method. This would only occur when an early-stage company raises development capital funding and the investors achieve a majority stake." [Zephyr Definition]. Management buyout is an indicator variable equal to one if "All or some of the existing management of the company buy at least 50% of the company from its existing owners." A private equity company is often brought in to aid the purchase through provision of equity funding. A 'new company' (newco) is normally formed by the management team specifically to purchase the Target. The acquirer company would show 'MBO Team' unless the name of the newco is known. If the name of the newco has been released, this company would be entered as the acquirer. If the Private Equity firm backing the deal takes a majority stake in the Target, the deal is not defined as an MBO and would be coded as an IBO." [Zephyr Definition]

[Table 3.1 here]

3.3. Results

3.3.1. Summary Statistics

In Table 3.2 we present the descriptive statistics for the full sample. The firms targeted in the buyout transactions have on average 3.79 patents. Given the patent count variable is highly skewed we transform it into *ln(1+patent count)* in the regression analysis. The relative and absolute citations are comparable with previous studies and are 1.48 and 0.651, respectively. The mean number of Radical patents is 0.3 and the mean of Innovation efficiency is 0.62.

Our country level controls such as the measure of Intellectual Property Rights (IPR) has a mean of 8.1. The country innovativeness intensity (INV) measure implies that 1.286 patent applications are made per 100 million of GDP measured in US dollars. The equity market development has a mean value of 128.559. The mean credit market development measured as private credit to GDP (CMD1) is 136.632 and as domestic credit provided by financial sector to GDP (CDM2) is 165.548. The average GDP growth is 2.083.

We have a limited number of data at the firm level. Due to those limitations the sample size drops by almost a half. Yet, we decided to present some controls related to the financial position of the target firm. On average target firms have total sales of 10.63 million Euro, 37 years since incorporation and zero return on assets.

[Table 3.2 here]

3.3.2. Univariate Analysis

Table 3.3 presents univariate comparison of means tests and shows the comparison of various innovation metrics one year before the buyout to three years after the buyout. Panel A shows the results for radical patent applications. Panel B shows the results for patent citations. Panel C shows the results for innovation efficiency. We separate the tests into Institutional Buyouts, Management Buyouts and All Buyouts.

The data indicate that three years following Institutional Buyouts, firms reduce their radical patent applications by 27% compared to one year before the buyout. They also have significantly fewer patent citations (51% lower) and have decreased level of innovation efficiency (14% lower). On the other hand, firms that experienced a Management Buyout do not significantly change their radical patenting activity, citation intensity and innovation efficiency. Similar results were obtained from using Absolute citations and Relative citation measures in the place of the general citation measure (results not tabulated).

[Table 3.3 here]

Figure 3.1 graphs the mean of the number of patent application, radical patent applications, absolute citations and relative citations, from 3 years before the buyout event to three or five years after the event. Figure 3.1 shows that firms have a lower level of innovative activity following the buyout whether we consider the quantity or quality of patenting. We also notice that the innovation measures prior to the buyout are either constant or rising. This implies that it is not necessarily firms with lower level of innovative activity that are being targeted for buyouts.

[Figure 3.1 here]

Figure 3.2 graphs the mean level of innovation efficiency and the number of unique innovators, from three years before the buyout to five years after the buyout. We find that after buyout, the firms' innovation efficiency and number of unique innovators fall. This implies that despite reducing the number of innovators, innovation efficiency decreases because the rate of decrease in patenting is even higher than the rate of decrease in the number of unique innovators. Additionally, we observe that innovation efficiency remains constant before the buyout, while the number of unique innovators increases steadily.

[Figure 3.2 here]

3.3.3. Baseline Regressions

In the multivariate analysis we use patent count and citations as dependent variables. Given the patent count variable is highly skewed we transform it into *ln(1+patent count)* in the regression analysis. Considering the count nature of citations along with the over-dispersion observed in this variable, similar to other studies, we decided to use a negative binomial model.

In Table 3.4 we show the regressions of patent count on year dummies. In model (1) we use a simple pooled OLS regression and in model (2) and (3) we estimate a panel regression. In model (3) apart from country characteristics we also include firm controls, due to which the sample size drops quite significantly. We find there is a significant decline in the number of patent applications to the effect of 5 -11 % in year 2 and up to 17% in year 3 post buyout transaction.

The signs of coefficient estimate of other control variables are consistent with previous evidence. For example, IPR and INV have positive and significant effect on innovation.

Since patent counts only capture the quantity of innovative output, in the next sections we study the effect of buyouts on the quality of innovation by measuring citation activity.

[Table 3.4 here]

3.3.3.1 Buyouts and Innovation Quality

In Table 3.5 we show regressions using negative binomial model of citation count on year dummies. Year dummies of the patent filling relative to the buyout year are independent variables in all the models. In Panel A we present the results where we measure innovation quality using absolute citation, and in Panel B using relative citation. In model (1) we use a simple pooled OLS regression and in model (2) and (3) we estimate a panel regression. In model (2) we include country characteristics and in model (3) apart from country characteristics we also include firm level controls.

We find some evidence that just before the buyout transaction patents of the target firm are cited more heavily, yet after the buyout transaction the patents granted have fewer absolute as well as relative citation measures. The effect of drop in citation measures are particularly severe in year 2 and 3 after the buyout transaction. The negative effect is not only statistically significant but also economically sizable. For instance, for absolute citation models (1) – (3) indicate that the drop in absolute citation intensity in year 2 is 29%, while in year 3 it is between 26% and 61%. The relative citation models (1) – (3) indicate that the fall in innovation in year 3 is between 37% and 46%.

[Table 3.5 here]

3.3.4. Institutional and Management Buyouts

In this analysis, we distinguish between institutional and management buyouts. We expect that institutional investors are likely to have different incentives and long-term objectives than management buyouts. In Table 3.6 we present the results where we limit the sample to institutional buyouts only. We find that there is a very significant drop in both absolute and relative citations following institutional buyouts. Two years after the buyout event, absolute citations decrease around 35%. Three years after the buyout, the negative effect on innovation quality measures is further strengthened. We observe that absolute citations decrease between 31% and 42%, while relative citations fall between 43% and 48%.

[Table 3.6 here]

In Table 3.7 we show results where we include management buyouts only. The effect of buyouts on absolute and relative citations is much weaker in the case of management buyouts when compared to Institutional buyouts. Within model (1) and (2) of Panel A, we do not observe any statistically significant effect on absolute citations post buyout. Within model (3), we find a statistically significant negative effect one year after the buyout on absolute citation intensity. However, no statistically significant effects are observed on relative citations in models (1), (2) and (3). The results indicate that the negative effect from buyouts is predominantly observed for institutional buyouts and not management buyouts.

[Table 3.7 here]

3.3.5. Radical Innovation

Thus far we have analysed various general measures of innovation. However, the nature of innovation might differ. For example, certain patents might refer directly to scientific literature and be more radical in nature, while other patents might be just incremental in nature and improve the existing innovation, thus refer more to patent literature. We distinguish between the two and define radical innovation as the total number of patents granted to a firm i in the year t, which have at least one citation to a non-patent literature.

In order to identify the effect of buyouts on radical innovation we limit our sample to only those target firms that had at least one radical patent applied for and granted within a period of 3 years before to 3 years after the buyout.

We present the results in Table 3.8. We find that the number of radical innovations drops after buyout transaction. We observe a statistically and economically significant drop in radical innovation one, two and three years after the buyout. In year one, we see a drop of 4% of radical patents in model (3). The drop in radical innovation in year 2 is between 2 to 5% and in year 3 between 3 to 6%.

[Table 3.8 here]

3.3.6 Innovation Efficiency

This analysis considers how efficiently a firm utilizes its R&D team following the buyout. Innovation efficiency can be improved by either increasing the number of patent applications while keeping the size of the R&D team constant or by producing the same number of patent applications using a smaller R&D team.

The results for innovation efficiency are presented in Table 3.9. Panel A, show the results for the entire sample. Panel B, show the results for only Institutional Buyouts and

Panel C for only Management Buyouts. Similar to the findings from patent counts, radical patent counts, absolute citations and relative citations, we find that institutional buyouts have the most significant negative effect on innovation efficiency. The decrease in innovation efficiency ranges between 17% for Institutional buyouts to 15% for Management buyouts, three years after the buyout.

[Table 3.9 here]

3.4. Additional Analysis

3.4.1. Method of Financing: Private Equity

The method of financing a deal can vary, some deals are just financed with resources from limited partners, and others can be financed through combination of private equity and debt. We therefore here limit the sample to deals that are exclusively financed with private equity. We thus intend to make it comparable with previous studies such as Lerner, Sorensen, and Strömberg (2011). In Table 3.10, columns (1) and (2) have absolute citations as their dependent variable, while columns (3) and (4) have relative citations as their dependent variables. Columns (1) and (3) include only Pre-2006 deals while columns (2) and (4) include only Post-2006 deals.

Comparing our sample with Lerner, Sorensen, and Strömberg (2011) is not straightforward as the datasets are quite different and Lerner, Sorensen, and Strömberg (2011) dataset finishes in 2006 and is a US only study. We therefore obtain a US only sample, and split this sub-sample into two periods: before and after 2006. Columns 1 and 3, within Panel A of Table 3.10, includes deals that are most similar *to* Lerner, Sorensen, and Strömberg (2011) study. Pre-2006, for the US only sample, we do not observe a statistically significant positive or negative effect of buyouts on either absolute or relative citation intensity. In column 2 and

4 we include deals post 2006. It looks like quite significant changes happened in the nature of deals after 2006 and the negative effect of buyouts on innovation that we obtain are present strongly in the post 2006 period.

In Panel B, of Table 3.10, we study international Private equity sample and find that similar to the US Private Equity deals only results, the negative effect of buyouts is limited to the post-2006 period. The negative effect is also weaker for Private equity only sample.

In Panel C, of Table 3.10, we analyse the absolute and relative citation intensity of all deals pre and post 2006. We find that while the negative effect on innovation is more significant post-2006, we do find some negative effect pre-2006 as well, such as in the case of Absolute citations in model (3) during year 2 and year 3.

[Table 3.10 here]

3.4.2. Subsample Analysis

In our sample several countries dominate in terms of the domicile of the most innovative firms. To verify whether our results are not driven by a subsample set of countries we run regressions including only Germany, UK and US in Table 3.11. We find a similar pattern that the investment in innovation drops after the buyout transaction. We also check if the results hold if we exclude those countries i.e. Germany, UK and US, and find significant drop in innovative activity after the buyout transaction.

[Table 3.11 here]

I did a propensity score matching analysis between firms that went through a public to private transaction (the treated firms) and those firms who got an offer to be taken private, but this offer was eventually withdrawn (the untreated firms). The results for this study have not been tabulated. There were very few deals within the withdrawn category. The results were however, consistent with the findings in the paper.

3.5. Conclusion

This paper studies the impact of public to private buyout transactions on the innovation activity of target firms. We analyzed both quantity and quality of patenting activity. We find that following buyouts, firms produce fewer patents overall, fewer radical innovations and receive fewer citations on the patents produced. In addition, buyouts also have a negative effect on innovation efficiency, despite reducing the number of innovators in the firm following the buyout. The negative effects on innovation are more pronounced for institutional buyouts compared to management buyouts, and for post-2006 period compared to pre-2006 period.

Figure 3.1. Change in Innovation metrics

Figure 3.1 shows the change in various innovation metrics starting three years before the public to private transaction event (T-3) to 3 or 5 years after the event (T+3 / T+5). In Panel A, we consider the mean number patent application each year. In Panel B, we consider the mean number of only radical patents. In Panel C, we consider the mean number of Absolute citations received by patents applied for in that year. In Panel D, we consider the mean relative citations received by patents applied for in that year. See Table 3.1 for the sample description and Appendix Table 3.AII for the variable definitions.

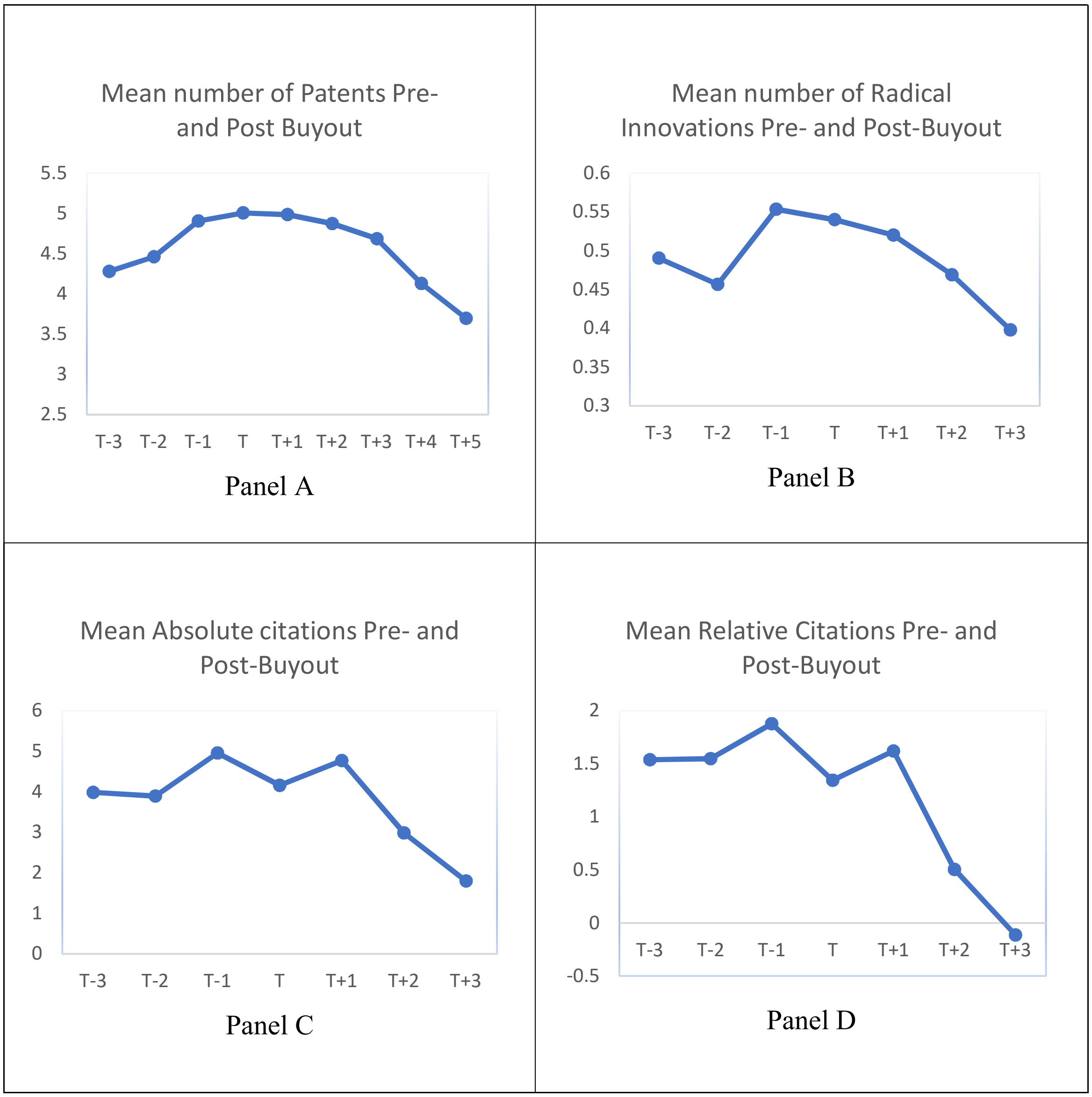


Figure 3.2. Change in Innovation Efficiency metrics

Figure 1 shows the change in various innovation efficiency metrics starting three years before the public to private transaction event (T-3) to 5 years after the event (T+3 / T+5). In Panel A, we consider the mean Innovation Efficiency pre- and post-buyout. In Panel B, we consider the mean number of Innovators pre- and post-buyout. See Table 3.1 for the sample description and Appendix Table 3.AII for the variable definitions.

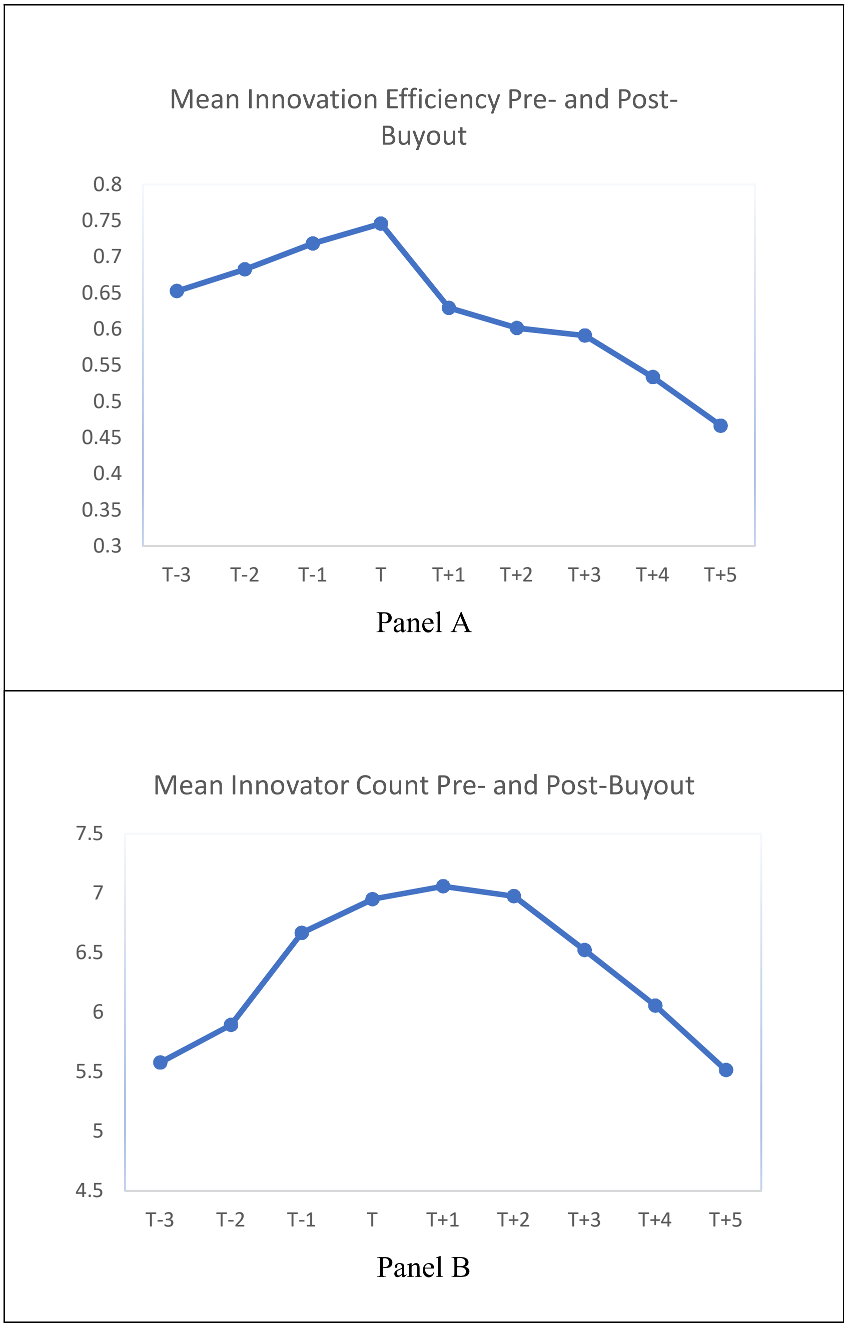


Table 3.1. Sample Distribution

This table presents the sample construction and the distribution of sample by announcement year (Panel A), target industry (Panel B), target country (Panel C), and by deal type (Panel D) for deals announced in 1997-2011 with at least one patent granted to the target firm 3 years before to 3 years after the transaction.

Panel A: Distribution by year

Year	Deals #	Patents #	Mean Innovation Efficiency	Deals # with Radical Patents	Radical Patent #
1997	29	1,266	0.5437	5	91
1998	43	661	0.6922	8	43
1999	62	713	0.4975	16	35
2000	62	3,107	0.5942	19	152
2001	63	2,502	1.0325	25	177
2002	83	2,634	0.7069	26	155
2003	128	6,319	0.7999	56	745
2004	146	3,075	0.6338	56	196
2005	190	6,631	0.6439	68	294
2006	174	7,114	0.6738	57	1,210
2007	232	11,184	0.6338	75	963
2008	133	2,437	0.5890	39	111
2009	68	1,459	0.5568	26	142
2010	98	1,317	0.6208	29	111
2011	110	3,380	0.6792	38	255
Total	1,621	53,799	0.6602	543	4,680

Panel B: Distribution by industry

Industry	Deals#	Patents#	Mean Innovation Efficiency	Deals# with Radical Patents	Radical Patents
Agriculture (00-09)	6	123	0.5052	5	10
Mining (10-14)	18	68	0.4311	1	1
Construction (15-17)	6	967	0.4914	2	192
Manufacturing (20-39)	1,255	47,988	0.7197	397	3,841
Transportation, Communications (40-49)	10	284	0.6064	5	8
Wholesale Trade (50-51)	26	241	0.4866	5	25
Retail Trade (52-59)	219	3,439	0.4583	103	523
Finance, Insurance, and Real Estate (60-67)	34	212	0.3400	15	30
Services (70-89)	47	477	0.4819	10	50
Total	1,621	53,799	0.6602	543	4,680

Panel C: Distribution by target's country

Country	Deals #	Patents #	Mean Innovation Efficiency	Deals# with Radical Patents	Radical Patents
AT Austria	21	361	0.9281	5	11
AU Australia	7	40	0.3332	2	8
BE Belgium	17	301	0.6713	2	6
BR Brazil	1	1	0.1429	0	0
CA Canada	34	2,911	0.6037	16	198
CH Switzerland	28	641	0.7203	5	12
CN China	3	89	0.3859	0	0
CZ Czech Republic	8	21	0.1278	0	0
DE Germany	243	12,588	1.0159	102	716
DK Denmark	21	355	0.9100	5	10
ES Spain	28	392	0.9071	3	3
FI Finland	35	267	0.4405	1	1
FR France	187	4,270	0.8023	29	72
GB UK	266	3,282	0.5379	61	177
IE Ireland	1	7	0.7143	0	1
IL Israel	5	307	0.5029	3	30
IT Italy	47	1,106	0.7389	6	25
JP Japan	17	3,214	0.5074	10	246
KR Korea Republic	8	681	0.5351	1	1
KY Cayman Islands	1	1	0.0714	0	0
LT Lithuania	1	1	0.0714	0	0
LU Luxemburg	3	208	1.3227	1	9
MX Mexico	2	3	0.2143	0	1
NL Netherlands	64	572	0.5200	20	23
NO Norway	14	133	0.5108	5	9
NZ New Zealand	2	9	0.2229	1	1
PL Poland	2	48	1.1637	0	0
PT Portugal	1	3	0.4286	0	0
RO Romania	1	3	0.4286	0	0
RU Russia	1	4	0.0571	0	0
SE Sweden	47	2,363	0.7220	17	112
SG Singapore	3	283	0.5408	2	45
SI Slovenia	1	1	0.1429	0	0
TW Taiwan	2	527	1.1454	0	0
US United States	496	18,786	0.5143	245	2,964
ZA South Africa	3	20	0.4841	1	1
Total	1,621	53,799	0.6602	543	4,680

Panel D: Distribution by deal type

Deal type	Deals #	Patents #	Mean Innovation Efficiency	Deals# with Radical Patents	Radical Patents
Institutional Buyout	1,169	44,225	0.6925	107	681
Management Buyout	452	9,574	0.5767	436	3,999
Total	1,621	53,799	0.6602	543	4,680

Table 3.2. Summary Statistics

This table presents summary statistics for deals announced in 1997-2011 with at least one patent granted to the target firm 3 years before to 3 years after the transaction.

Variable	# of Deals	# of Deal-years	Mean	S.D.	25%	Median	75%
Innovation Variables							
Patent count	10,829	1,547	3.7869	10.2709	0.0000	1.0000	3.0000
Radical Patent count	10,829	1,547	0.2968	1.1129	0.0000	0.0000	0.0000
Citations	10,829	1,547	5.6396	25.7136	0.0000	0.0000	0.0000
Absolute citation	10,829	1,547	1.4808	6.7374	0.0000	0.0000	0.0000
Relative Citation	10,829	1,547	0.6481	3.5782	0.0000	0.0000	0.0000
Innovation efficiency	10,829	1,547	0.6149	0.9134	0.0000	0.2500	1.0000
Country-level Variables							
IPR	10,794	1,542	8.0992	0.5909	8.0000	8.2000	8.3000
INV	10,689	1,527	1.2856	1.2062	0.6249	1.3483	1.6006
EMD	10,388	1,484	128.5589	86.0556	60.7588	103.0314	196.9813
CMD1	10,829	1,547	136.6320	46.5264	96.7833	126.8692	183.9363
CDM2	10,829	1,547	165.5480	51.4744	126.6678	155.5680	213.4666
GDP_GR	10,829	1,547	2.0830	1.8671	1.6015	2.3749	3.2014
Firm-level Variables							
SIZE	4,641	663	10.6266	1.9061	9.6004	10.6065	11.7019
AGE	9,646	1378	36.6582	29.2099	18.0000	27.0000	47.0000
ROA	4,592	656	-0.0034	0.8026	-0.0104	0.0534	0.1363

Table 3.3 Comparison of change in Innovation measure following Buyout

Table 3.3 compares various measures of innovation one year before buyout transaction to 3 years after the buyout transaction, for all types of buyout, Institutional buyouts and Management buyouts. ***(**)(*) denotes significance at the 1%(5%)(10%) two-tailed level.

	N	Institutional Buyouts	N	Management Buyouts	N	All Buyouts
Panel A: Number of Radical Patent Applications						
One year before buyout (t-1) [A]	1,102	0.3303085	439	0.1594533	1,541	0.2816353
Three years after buyout (t+3) [B]	1,102	0.2413793	439	0.1480638	1,541	0.2147956
Difference [A] - [B]		**0.0889292** **		**0.0113895**		**0.0668397** **
Panel B: Number of Patent Citations						
One year before buyout (t-1) [A]	1,102	6.76225	439	2.954442	1,541	5.677482
Three years after buyout (t+3) [B]	1,102	3.314882	439	1.851936	1,541	2.898118
Difference [A] - [B]		**3.447368** ***		**1.102506**		**2.779364** ***
Panel C: Innovation efficiency						
One year before buyout (t-1) [A]	1,102	0.6718388	439	0.5533803	1,541	0.6380924
Three years after buyout (t+3) [B]	1,102	0.5767191	439	0.6216192	1,541	0.5895102
Difference [A] - [B]		**0.0951198** ***		**-0.0682389**		**0.0485822** *

Table 3.4. Estimates of Patent Count

This table presents regressions where the dependent variable is the ln(1+patents granted to the target firm). In model (1) we present pooled OLS regression, in model (2) and (3) panel regression. In all models we show the regression where the independent variables are the relative years pre and post to the buyout transaction (event year 0 is the omitted base category with a coefficient normalized to one). All variables are defined in Appendix. ***, **, and * represent 1%, 5%, and 10% significance levels respectively. Marginal effects are reported.

		(1)		(2)		(3)
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Event year −3	-0.0667*	[-1.82]	-0.0692***	[-3.16]	-0.0353	[-0.96]
Event year −2	-0.0423	[-1.16]	-0.0439**	[-2.00]	-0.0191	[-0.52]
Event year −1	-0.0379	[-1.04]	-0.0389*	[-1.77]	-0.0478	[-1.29]
Event year 1	-0.0229	[-0.63]	-0.0320	[-1.46]	-0.0804**	[-2.18]
Event year 2	-0.0408	[-1.12]	-0.0529**	[-2.42]	-0.1136***	[-3.07]
Event year 3	-0.0731**	[-2.00]	-0.0853***	[-3.89]	-0.1744***	[-4.72]
IPR			0.0423	[1.00]	0.0825	[1.35]
INV			0.1491***	[6.41]	0.0953**	[2.00]
EMD			-0.0004	[-1.07]	-0.0001	[-0.09]
CMD1			-0.0023*	[-1.85]	-0.0034*	[-1.69]
CDM2			0.0012	[1.04]	0.0017	[0.84]
GDP_GR			-0.0076	[-0.57]	0.0033	[0.15]
SIZE					0.1016***	[4.39]
AGE					0.0408	[0.67]
ROA					-0.0409	[-0.91]
Obs.	10297		9688		3584	

Table 3.5. Negative Binomial Estimates of Citations (All Buyouts)

This table presents regressions where the dependent variable is citation count measured by absolute citations in Panel A and relative citations in Panel B. In model (1) we present pooled regression, in model (2) and (3) panel regression. In all models we show the regression where the independent variables are the relative years pre and post to the buyout transaction (event year 0 is the omitted base category with a coefficient normalized to one). All variables are defined in Appendix. ***, **, and * represent 1%, 5%, and 10% significance levels respectively. Marginal effects are reported.

Panel A. Absolute citations

	(1)		(2)		(3)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Event year −3	-0.0256	[-0.13]	-0.1448	[-1.38]	-0.2282	[-1.29]
Event year −2	-0.1861	[-0.93]	-0.2356**	[-2.21]	-0.1572	[-0.90]
Event year −1	0.0009	[0.00]	-0.0522	[-0.51]	-0.0518	[-0.30]
Event year 1	-0.0799	[-0.40]	-0.0467	[-0.45]	-0.1391	[-0.80]
Event year 2	-0.2898	[-1.45]	-0.2510**	[-2.34]	-0.2399	[-1.35]
Event year 3	-0.4785**	[-2.39]	-0.3055***	[-2.73]	-0.4039**	[-2.12]
IPR			0.1015	[1.25]	0.0945	[0.89]
INV			0.2883***	[5.88]	0.4650***	[4.88]
EMD			-0.0013	[-1.61]	0.0009	[0.57]
CMD1			-0.0023	[-0.74]	-0.0078	[-1.64]
CDM2			0.0033	[1.22]	0.0027	[0.56]
GDP_GR			0.0055	[0.22]	-0.0207	[-0.51]
SIZE					0.1487***	[3.26]
AGE					0.2953**	[2.48]
ROA					0.6421**	[1.98]
Obs.	10297		9051		3290	

Panel B. Radical citations.

	(1)		(2)		(3)	
Event year −3	-0.0005	[-0.00]	0.0080	[0.06]	-0.2752	[-1.09]
Event year −2	-0.1717	[-0.67]	-0.1346	[-0.95]	-0.0793	[-0.33]
Event year −1	-0.0305	[-0.12]	0.0632	[0.47]	0.1281	[0.55]
Event year 1	-0.1454	[-0.56]	-0.0599	[-0.43]	-0.0009	[-0.00]
Event year 2	-0.3050	[-1.18]	-0.1260	[-0.89]	-0.0721	[-0.30]
Event year 3	-0.6020**	[-2.32]	-0.4651***	[-3.03]	-0.6154**	[-2.20]
IPR			0.0298	[0.30]	0.1655	[1.18]
INV			0.1524**	[2.40]	0.0610	[0.60]
EMD			0.0015	[1.64]	0.0009	[0.50]
CMD1			0.0061	[1.64]	-0.0031	[-0.61]
CDM2			-0.0026	[-0.77]	0.0083	[1.63]
GDP_GR			0.0527*	[1.68]	0.1227**	[2.36]
SIZE					0.1663***	[2.87]
AGE					0.0854	[0.58]
ROA					1.0699**	[2.48]
Obs.	10297		9688		3584	

Table 3.6. Negative Binomial Estimates of Citation (Institutional Buyouts)

This table presents regressions where the dependent variable is citation count measured by absolute citations in Panel A and relative citations in Panel B. In model (1) we present pooled regression, in model (2) and (3) panel regression. In all models we show the regression where the independent variables are the relative years pre and post to the buyout transaction (event year 0 is the omitted base category with a coefficient normalized to one). All variables are defined in Appendix. ***, **, and * represent 1%, 5%, and 10% significance levels respectively. Marginal effects are reported.

Panel A. Absolute citations

		(1)		(2)		(3)
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Event year −3	-0.0188	[-0.08]	-0.1101	[-0.92]	-0.2019	[-0.94]
Event year −2	-0.2274	[-1.01]	-0.2369*	[-1.93]	-0.1644	[-0.78]
Event year −1	-0.0515	[-0.23]	-0.0320	[-0.27]	0.0654	[0.32]
Event year 1	-0.0876	[-0.39]	0.0061	[0.05]	0.0825	[0.41]
Event year 2	-0.3681	[-1.63]	-0.2989**	[-2.39]	-0.3257	[-1.48]
Event year 3	-0.5443**	[-2.40]	-0.3759***	[-2.91]	-0.4312*	[-1.91]
IPR			0.0029	[0.03]	0.0178	[0.15]
INV			0.2117***	[4.83]	0.2972*	[1.91]
EMD			-0.0015*	[-1.69]	0.0008	[0.41]
CMD1			-0.0002	[-0.07]	-0.0031	[-0.39]
CDM2			0.0015	[0.52]	-0.0031	[-0.39]
GDP_GR			-0.0165	[-0.61]	-0.0438	[-0.92]
SIZE					0.1290**	[2.38]
AGE					0.2982**	[2.11]
ROA					0.3173	[0.87]
Obs.	7322		6237		2177	

Panel B. Relative citations

	(1)		(2)		(3)	
Event year −3	-0.0052	[-0.02]	-0.0704	[-0.45]	-0.1129	[-0.38]
Event year −2	-0.2191	[-0.75]	-0.2159	[-1.33]	0.1423	[0.51]
Event year −1	-0.1058	[-0.36]	0.0162	[0.11]	0.3138	[1.15]
Event year 1	-0.1930	[-0.66]	-0.0380	[-0.24]	0.1838	[0.66]
Event year 2	-0.4409	[-1.51]	-0.2324	[-1.43]	-0.1468	[-0.50]
Event year 3	-0.6490**	[-2.22]	-0.5579***	[-3.15]	-0.6177*	[-1.83]
IPR			-0.0700	[-0.64]	0.1727	[1.07]
INV			0.1449*	[1.72]	0.2758	[1.40]
EMD			0.0007	[0.68]	-0.0007	[-0.30]
CMD1			0.0099*	[1.90]	-0.0119	[-1.60]
CDM2			-0.0039	[-0.83]	0.0192**	[2.48]
GDP_GR			0.0213	[0.60]	0.1115*	[1.76]
SIZE					0.1467**	[2.04]
AGE					0.1417	[0.81]
ROA					0.7467	[1.49]
Obs.	7322		6237		2436	

Table 3.7. Negative Binomial Estimates of Citation (Management Buyouts)

This table presents regressions where the dependent variable is citation count measured by absolute citations in Panel A and relative citations in Panel B. In model (1) we present pooled regression, in model (2) and (3) panel regression. In all models we show the regression where the independent variables are the relative years pre and post to the buyout transaction (event year 0 is the omitted base category with a coefficient normalized to one). All variables are defined in Appendix. ***, **, and * represent 1%, 5%, and 10% significance levels respectively. Marginal effects are reported.

Panel A. Absolute citations

	(1)		(2)		(3)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Event year −3	-0.0736	[-0.18]	-0.1922	[-1.17]	-0.3481	[-1.24]
Event year −2	0.0585	[0.14]	-0.0596	[-0.37]	-0.1093	[-0.38]
Event year −1	0.3009	[0.72]	-0.0511	[-0.32]	-0.3111	[-1.09]
Event year 1	-0.0288	[-0.07]	-0.1485	[-0.91]	-0.6080*	[-1.71]
Event year 2	0.1264	[0.30]	-0.1499	[-0.93]	-0.1830	[-0.67]
Event year 3	-0.1165	[-0.28]	0.0354	[0.22]	-0.1134	[-0.32]
IPR			0.8181**	[2.32]	0.2706	[0.84]
INV			0.6818***	[5.08]	0.5346***	[2.70]
EMD			-0.0019	[-0.86]	0.0046	[1.03]
CMD1			-0.0029	[-0.51]	-0.0039	[-0.60]
CDM2			0.0064	[1.07]	0.0035	[0.49]
GDP_GR			0.0827	[1.31]	0.0458	[0.57]
SIZE					0.2667**	[2.45]
AGE					0.3143	[1.33]
ROA					2.1789***	[2.86]
Obs.	2975		2898		1148	

Panel B. Relative citations

	(1)		(2)		(3)	
Event year −3	0.0587	[0.11]	-0.1360	[-0.42]	-0.6676	[-1.33]
Event year −2	0.2991	[0.56]	-0.1580	[-0.48]	-0.8366	[-1.64]
Event year −1	0.6328	[1.20]	0.1921	[0.63]	-0.3828	[-0.83]
Event year 1	0.3263	[0.61]	-0.1690	[-0.51]	-0.5547	[-1.11]
Event year 2	0.6695	[1.27]	0.1581	[0.52]	0.1418	[0.35]
Event year 3	-0.1348	[-0.25]	-0.1892	[-0.57]	-0.7052	[-1.39]
IPR			1.1445**	[2.35]	0.8038	[1.36]
INV			0.1046	[0.74]	-0.0293	[-0.15]
EMD			0.0063**	[2.48]	0.0104	[1.64]
CMD1			0.0011	[0.15]	-0.0033	[-0.35]
CDM2			-0.0004	[-0.06]	0.0030	[0.28]
GDP_GR			0.0842	[1.03]	0.0491	[0.45]
SIZE					0.2516*	[1.81]
AGE					0.1034	[0.31]
ROA					1.8502*	[1.90]
Obs.	2975		2898		1148	

Table 3.8. Estimates of Radical Patent Count

This table presents regressions where the dependent variable is the ln(1+radical patents granted to the target firm). In model (1) we present pooled OLS regression, in model (2) and (3) panel regression. In all models we show the regression where the independent variables are the relative years pre and post to the buyout transaction (event year 0 is the omitted base category with a coefficient normalized to one). All variables are defined in Appendix. ***, **, and * represent 1%, 5%, and 10% significance levels respectively. Marginal effects are reported.

		(1)		(2)		(3)
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Event year −3	-0.0051	[-0.37]	-0.0043	[-0.43]	0.0075	[0.48]
Event year −2	-0.0035	[-0.25]	-0.0034	[-0.34]	0.0017	[0.11]
Event year −1	-0.0040	[-0.29]	-0.0036	[-0.36]	-0.0075	[-0.48]
Event year 1	-0.0134	[-0.96]	-0.0145	[-1.45]	-0.0378**	[-2.44]
Event year 2	-0.0182	[-1.31]	-0.0184*	[-1.84]	-0.0450***	[-2.90]
Event year 3	-0.0347**	[-2.51]	-0.0385***	[-3.86]	-0.0607***	[-3.92]
IPR			0.0310**	[2.10]	0.0453**	[2.23]
INV			0.0421***	[5.14]	0.0401**	[2.53]
EMD			0.0002	[1.39]	0.0005	[1.59]
CMD1			0.0004	[0.96]	0.0008	[1.17]
CDM2			-0.0001	[-0.28]	-0.0004	[-0.64]
GDP_GR			-0.0012	[-0.25]	-0.0036	[-0.49]
SIZE					0.0264***	[3.44]
AGE					0.0049	[0.24]
ROA					-0.0198	[-1.34]
Obs.	10297		9688		3584	

Table 3.9. Estimates of Innovation Efficiency

This table presents regressions where the dependent variable is innovation efficiency. In model (1) we present pooled OLS regression, in model (2) and (3) panel regression. In all models we show the regression where the independent variables are the relative years pre and post to the buyout transaction (event year 0 is the omitted base category with a coefficient normalized to one). All variables are defined in Appendix. ***, **, and * represent 1%, 5%, and 10% significance levels respectively. Marginal effects are reported.

Panel A. All Sample

	(1)		(2)		(3)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Event year −3	-0.0096	[-0.28]	-0.0129	[-0.44]	0.0660	[1.30]
Event year −2	0.0202	[0.59]	0.0117	[0.40]	0.0280	[0.55]
Event year −1	-0.0041	[-0.12]	-0.0086	[-0.29]	-0.0255	[-0.50]
Event year 1	-0.0372	[-1.09]	-0.0603**	[-2.04]	-0.0683	[-1.35]
Event year 2	-0.0590*	[-1.74]	-0.0758**	[-2.57]	-0.0789	[-1.56]
Event year 3	-0.0657*	[-1.94]	-0.0746**	[-2.53]	-0.1800***	[-3.56]
IPR			0.0893***	[3.10]	0.0655	[1.52]
INV			0.0027	[0.17]	-0.0481	[-1.43]
EMD			-0.0005*	[-1.81]	-0.0008	[-1.21]
CMD1			-0.0028***	[-3.26]	-0.0033**	[-2.34]
CDM2			0.0011	[1.44]	0.0021	[1.44]
GDP_GR			-0.0014	[-0.15]	0.0055	[0.36]
SIZE					0.0283*	[1.74]
AGE					0.0013	[0.03]
ROA					0.0133	[0.42]
Obs.	10297		9688		3584	

Panel B. Institutional Buyouts

	(1)		(2)		(3)	
Event year −3	-0.0114	[-0.28]	-0.0155	[-0.43]	0.0741	[1.21]
Event year −2	0.0162	[0.39]	0.0086	[0.24]	0.0026	[0.04]
Event year −1	-0.0005	[-0.01]	-0.0047	[-0.13]	0.0218	[0.36]
Event year 1	-0.0207	[-0.50]	-0.0514	[-1.44]	-0.0232	[-0.38]
Event year 2	-0.0617	[-1.50]	-0.0826**	[-2.31]	-0.0628	[-1.03]
Event year 3	-0.1041**	[-2.53]	-0.1125***	[-3.14]	-0.1902***	[-3.11]
IPR			0.0855***	[2.60]	0.0517	[1.01]
INV			-0.0012	[-0.06]	-0.0394	[-1.00]
EMD			-0.0011***	[-3.32]	-0.0011	[-1.43]
CMD1			-0.0008	[-0.73]	-0.0016	[-0.81]
CDM2			-0.0000	[-0.03]	0.0007	[0.38]
GDP_GR			-0.0033	[-0.30]	0.0049	[0.25]
SIZE					0.0125	[0.60]
AGE					-0.0178	[-0.33]
ROA					0.0216	[0.61]
Obs.	7322		6790		2436	

Panel C. Management Buyouts

	(1)		(2)		(3)	
Event year −3	-0.0050	[-0.08]	-0.0068	[-0.13]	0.0486	[0.54]
Event year −2	0.0300	[0.50]	0.0189	[0.36]	0.0820	[0.91]
Event year −1	-0.0131	[-0.22]	-0.0175	[-0.34]	-0.1257	[-1.39]
Event year 1	-0.0778	[-1.31]	-0.0809	[-1.56]	-0.1640*	[-1.81]
Event year 2	-0.0525	[-0.88]	-0.0597	[-1.15]	-0.1129	[-1.25]
Event year 3	0.0287	[0.48]	0.0143	[0.28]	-0.1584*	[-1.75]
IPR			0.2078***	[3.06]	0.1894**	[2.17]
INV			0.0018	[0.05]	-0.1100	[-1.57]

EMD		0.0008	[1.37]	0.0014	[1.00]
CMD1		-0.0047***	[-3.54]	-0.0057***	[-2.81]
CDM2		0.0012	[0.86]	0.0038	[1.61]
GDP_GR		-0.0070	[-0.43]	0.0074	[0.28]
SIZE				0.0633**	[2.10]
AGE				0.0437	[0.58]
ROA				0.1113	[1.15]
Obs.	2975	2898		1148	

Table 3.10. Comparison analysis with Lerner

This table presents regressions where the dependent variable is citation count measured by absolute citations in model (1) - (2) and relative citations in model (3) - (4). In all models we show the regression where the independent variables are the relative years pre and post to the buyout transaction (event year 0 is the omitted base category with a coefficient normalized to one). All variables are defined in Appendix. ***, **, and * represent 1%, 5%, and 10% significance levels respectively. Marginal effects are reported.

Panel A: Sample of US Private Equity deals (Lerner Sample)

	(1) Pre 2006		(2) Post 2006		(3) Pre 2006		(4) Post 2006	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Event year −3	0.1411	[0.50]	0.0633	[0.21]	0.0801	[0.23]	0.0126	[0.04]
Event year −2	-0.1219	[-0.41]	-0.2294	[-0.72]	-0.0902	[-0.24]	-0.0640	[-0.18]
Event year −1	0.1789	[0.63]	-0.5290	[-1.54]	0.4261	[1.30]	-0.5628	[-1.41]
Event year 1	0.2752	[0.99]	-0.2491	[-0.78]	0.2885	[0.84]	-0.3545	[-0.94]
Event year 2	-0.4743	[-1.44]	-0.6206*	[-1.77]	-0.2287	[-0.59]	-0.2885	[-0.78]
Event year 3	0.2328	[0.82]	-1.5152***	[-3.28]	0.4420	[1.33]	-1.7989***	[-2.87]
Obs.	756		945		756		945	

Panel B: All Private Equity deals

	(1) Pre 2006		(2) Post 2006		(3) Pre 2006		(4) Post 2006	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Event year −3	-0.1013	[-0.51]	0.0099	[0.05]	-0.1627	[-0.55]	0.2093	[0.78]
Event year −2	-0.2687	[-1.29]	-0.0979	[-0.47]	-0.1287	[-0.44]	0.0370	[0.13]
Event year −1	0.1756	[0.92]	-0.0709	[-0.34]	0.4255	[1.62]	0.0481	[0.18]
Event year 1	0.1586	[0.83]	0.1045	[0.53]	0.1942	[0.70]	0.0611	[0.22]
Event year 2	-0.2755	[-1.32]	-0.1252	[-0.60]	0.0181	[0.06]	0.0417	[0.15]
Event year 3	0.0654	[0.33]	-0.4313*	[-1.94]	0.3473	[1.28]	-0.9250***	[-2.63]
Obs.	2331		2842		2331		2842	

Panel C: All sample								
		(1)		(2)		(3)		(4)
		Pre 2006		Post 2006		Pre 2006		Post 2006
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Event year −3	-0.1473	[-1.04]	-0.0455	[-0.31]	-0.1666	[-0.83]	0.1672	[0.88]
Event year −2	-0.3048**	[-2.07]	-0.1174	[-0.80]	-0.1975	[-0.97]	-0.0492	[-0.25]
Event year −1	-0.0256	[-0.18]	-0.1119	[-0.76]	0.1884	[1.01]	-0.0193	[-0.10]
Event year 1	-0.1093	[-0.77]	-0.0454	[-0.31]	-0.1292	[-0.64]	0.0092	[0.05]
Event year 2	-0.3098**	[-2.11]	-0.2082	[-1.39]	-0.1685	[-0.84]	-0.0513	[-0.26]
Event year 3	-0.2431*	[-1.66]	-0.4542***	[-2.89]	-0.1561	[-0.77]	-0.7889***	[-3.35]
Obs.	4949		5348		4949		5348	

Table 3.11. Negative Binomial Estimated of Citation by Country

This table presents regressions where the dependent variable is citation count measured by absolute citations. In models (1) & (3) we limit the sample to US, UK or Germany, while in models (2) & (4) we limit the sample to all countries except US, UK or Germany. In models (1) & (2) absolute citations is the main dependent variable while in models (3) and (4) relative citations is the main dependent variable. In all models we show the regression where the independent variables are the relative years pre and post to the buyout transaction (event year 0 is the omitted base category with a coefficient normalized to one). ***, **, and * represent 1%, 5%, and 10% significance levels respectively. Marginal effects are reported.

	(1) US, UK & Germany only		(2) Excluding US, UK & Germany		(3) US, UK & Germany only		(4) Excluding US, UK & Germany	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Event year −3	0.0366	[0.18]	-0.1469	[-0.95]	0.0427	[0.17]	-0.1071	[-0.49]
Event year −2	0.0850	[0.43]	-0.0683	[-0.45]	0.1106	[0.45]	0.0717	[0.35]
Event year −1	0.0620	[0.31]	-0.0393	[-0.26]	0.2284	[0.95]	0.1707	[0.84]
Event year 1	-0.0692	[-0.34]	-0.1286	[-0.84]	-0.1847	[-0.70]	-0.0312	[-0.15]
Event year 2	-0.4561**	[-2.05]	-0.2357	[-1.50]	-0.4485	[-1.62]	-0.0865	[-0.41]
Event year 3	-0.6286***	[-2.72]	-0.4653***	[-2.83]	-0.9918***	[-3.03]	-0.7068***	[-2.80]
SIZE	0.0771	[1.45]	0.1443***	[4.17]	0.1995***	[3.25]	0.2663***	[5.81]
AGE	0.3624***	[2.67]	0.3171***	[3.01]	0.2312	[1.41]	0.1183	[0.89]
ROA	0.5743	[1.64]	0.4998*	[1.84]	0.2494	[0.64]	0.3088	[0.88]
Obs.	1386		4284		1386		4284	

Appendix

Table 3.AI. Sample Selection

	Number of observations
All buyouts	36,201
Zephyr matched with Orbis	21,296
Deals with patent data 3 years before and 3 years after transaction	2,468
Deals where the acquirer bought 100% of the target	1,621
After eliminating deals with missing data	1,471

Table 3.AII. Variable definitions

Variable	Definition	Data source
Innovation Measures		
Patent count	The total number of patents applied for and granted to firm i in year t.	PATSTAT
Radical innovation	The total number of patents granted to a firm i in the year t, which have at least one citation to a Non-Patent literature	PATSTAT
Citation count	The total number of citations received for patents filed and subsequently granted in the year t.	PATSTAT
Absolute citation	The total number of citations received for patents filed and subsequently granted during the year that a patent is granted and the following three periods.	PATSTAT
Relative citation	The total number of citations received for patents filed and subsequently granted during the year and the following three periods, less the average number of citations during this period that is received by matching patents.	PATSTAT
Innovation efficiency	The number application that has been filed and subsequently granted during the year, divided by the number of unique innovators.	PATSTAT
Country-level Characteristics		
IPR	Intellectual Property Rights measures aspects of intellectual property. In particular, protection of intellectual property, and additionally it reviews a country's policies and their effectiveness regarding patents, copyrights, and trademarks.	Park (2008)
INV	Country innovativeness measures as the number of resident patent applications scaled by GDP (in mln).	WDI/GDF database

EMD	Equity Market Development measured as the value of shares traded (the total number of shares traded, both domestic and foreign, multiplied by their respective matching prices) scaled by GDP.	WDI/GDF database
CMD1	Credit Market Development measured as domestic credit to private sector (% of GDP). Domestic credit to private sector refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment. Credit is an important link in money transmission; it finances production, consumption, and capital formation, which in turn affect economic activity.	WDI/GDF database
CMD2	Credit Market Development measured as domestic credit provided by financial sector (% of GDP). Domestic credit provided by the financial sector includes all credit to various sectors on a gross basis, with the exception of credit to the central government, which is net. The financial sector includes monetary authorities and deposit money banks, as well as other financial corporations where data are available (including corporations that do not accept transferable deposits but do incur such liabilities as time and savings deposits). Domestic credit provided by the financial sector as a share of GDP measures banking sector depth and financial sector development in terms of size.	WDI/GDF database
GDP_GR	GDP growth (annual %). Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2010 U.S. dollars. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of	WDI/GDF database

	fabricated assets or for depletion and degradation of natural resources.	
Firm-level Characteristics		
SIZE	Natural logarithm of operating revenue.	ORBIS
AGE	Natural logarithm of the number of years since the firm incorporation date.	ORBIS
ROA	Return on assets, defined as operating income before depreciation divided by total assets (book value of total assets).	ORBIS

Chapter 4

Pre-Going Private Ownership around the World

4.1. Introduction

Public to private buyout transactions (hereafter "going-private" or "buyout" transactions[1]) have grown in popularity around the world. For example, the Carlyle Group, one of the world's largest and most successful private equity organizations, highlighted in their 2013 Q2 Results: "We have been active in Asia, recently closing one and announcing another public to private transaction in China." Although, buyouts are supposed to create value by improving target firm efficiency (Guo, et al. 2011; Goergen et al., 2014a,b; Brewster et al., 2017), at different points in time, buyout transactions have been criticized in the media and have even been banned in some countries such as Italy. There has been growing concern in the media around the world that buyouts should be regulated. In 2006, for example, *The NY Times* reported that "LBOs should be illegal".[2] In 2007, *The Economist* stated that private equity funds need regulation.[3] German governmental officials have characterized private equity firms as "locusts".[4] Yet, an active buyout market for corporate control also serves a role of external corporate governance, and its aim is to improve efficiency. Introducing regulation might distort the governance role of the buyout funds as external monitors.

Although going private transactions have been widely studied in different countries (DeAngelo et al., 1984; Lehn and Poulsen, 1989; Halpern et al., 1999; Renneboog and Vensteenkiske, 2017), and ownership structures vary widely in different countries (Faccio and Lang, 2002), there is scant work that examines ownership structure and shareholder rights prior to going private in an international setting, apart from the continental European evidence of

Achleitner et al. (2013). The worldwide growth in buyout funds taking firms private gives rise to question about whether there are differences in the ownership structure of firms prior to going private in different countries. Ownership naturally affects internal and external corporate governance. Different types of owners have different incentives in terms of how they affect a firm's corporate policies (Connelly, et al. 2010; Anderson, et al. 2012; Coffee and Palia, 2016; McCahery and Vermeulen, 2016; Wood and Brewster, 2016), how efficiently they run the company, and also how they make decisions on whether to sell off the firm.

Given that buyout funds seek to improve a firm's efficiency, we claim that firms with certain ownership structure might be more likely to be taken private. Also, the way they are taken private might differ, as well. In order to assess the validity of these claims, it is helpful to understand whether or not shareholder ownership is systematically different before going private. Are public to private transactions more common for firms with block ownership? Do they differ depending on the buyout type?

Furthermore, a buyout typically involves leveraging the target company to a significant extent. The leverage creates an agency conflict between the investors in the target firm and its debtholders (Sherwin, 1988). When the target firm is restructured and left with sufficient funds to pay back its debt, it does not harm the creditors. However, the protection of creditors' rights becomes critical when the target firm is left insolvent or without necessary funds in order to sustain its operations.

Bankruptcy risk and expected agency costs are more relevant in the case of whole firm institutional buyouts than buildup strategies where the transaction was completed in several stages. Stronger creditor rights clarify and strengthen the lender's legal remedies, and, therefore, increase the supply of capital for institutional buyouts. In the absence of strong creditor rights, it could be harder to secure the requisite amount of debt finance, and build-up strategies may be more likely due to financial constraints. Also, in the case of management buyouts, information asymmetries for the new management team are less pronounced (Howorth et al., 2004), which mitigates the need to have stronger creditor rights to bring about completed deals.

We also examine whether legal conditions mitigate the probability of going private transactions. Better legal conditions ensure stronger certainty about the quality of exchanges and trading, thereby improving liquidity and lowering the cost of equity capital for publicly traded firms. As such, better legal conditions increase the likelihood of a firm being public and reduce the likelihood of a going private transaction.

Another concern about going private transactions is the possibility that they may lead to potential expropriation of minority shareholders through non-arms-length transactions. Going private imposes two primary costs for minority shareholders: lack of liquidity, and lack of transparency. In effect, a going private transaction potentially enables majority shareholders to extract greater rents from minority shareholders (DeAngelo, et al. 1984). Such misappropriation may happen even in developed countries, such as Canada and the U.S.[5] While the legal system in developed countries affords protections to shareholders in ways that mitigates the likelihood of such activity and provides redress in the event that it occurs, there is much more scope for opportunistic behavior in countries that do not afford such protections to minority shareholders. We, therefore, study whether there are any systematic differences in terms of country characteristics before going private transaction.

We examine these issues with a sample of 778 going private transactions between 2002 and 2014 from 36 countries, including Australia, Belgium, Bulgaria, Canada, China, Denmark, Finland, France, Germany, Greece, Honk Kong, Hungary, India, Ireland, Israel, Italy, Japan, the

Republic of Korea, Lithuania, Malaysia, the Netherlands, New Zealand, Norway, the Philippines, Poland, Portugal, the Russian Federation, Singapore, South Africa, Spain, Sweden, the United Kingdom, and the United States of America.

We find that going private transactions are more likely if the firm is owned by institutional or corporate investors and less likely if it is owned by family. The data show strong and consistent evidence that pre-going private ownership is characterized by block corporate or institutional investor ownership, where block ownership is defined as a shareholder with 10% stake in the company in the year prior to going private. We find that going private through a buildup strategy is less likely if the firm is owned by family, while management buyouts are more likely when the firm is owned by a corporate investor.

Stronger creditor rights increase the probability of going private, especially in the case of whole company and institutional buyouts. We also find that the legal conditions decrease the likelihood of going private for those buyout types. While the results might be affected by potential endogeneity problems, we try to mitigate these by running several robustness tests and find largely consistent evidence.

We contribute to the management literature by analyzing ownership differences in public to private transactions in an international context. Our paper focuses on ownership differences and provides evidence from a multi-country setting to understand the association between law, institutions, and ownership on the probability of public to private buyouts.

This paper is organized as follows. Section II summarizes the hypotheses. The data are introduced in Section III. The summary statistics and univariate tests are discussed in Section IV. Multivariate analyses and limitations are discussed in Section V. Concluding remarks follow in Section VI.

4.2. Theory and Hypotheses

The separation of ownership and control might be a major motive to extract private benefits by entrenched managers. Jensen (1986) claims that entrenched managers might not act in the best interest of existing shareholders. They might misuse the company's resources for empire building or to invest in negative NPV value projects. These agency costs might be more severe where the separation between the owners and management is more pronounced.

Aslan and Kumar (2011) claim that agency-cost theories explain the decision to go private. Ljungqvist, et al. (2016) analyze the consequences of public to private transactions when the incentives to sell become misaligned. Ownership structure is a central part of their model. They claim that shareholders in public companies do not internalize the consequences of their decision to sell to the wider economy; therefore, it has negative consequences for the economy. Renneboog, et al. (2007) show that shareholders in the UK receive a premium that results from firm undervaluation and incentive realignment. Mehran and Peristiani (2010) claim that the main reason for going private is due to poor financial visibility. Boot, et al. (2008) show in a theoretical model that firm ownership and investor participation are important determinants of a going private decision. Achleitner, et al. (2013) study how corporate control affects the likelihood of private equity acquisition for a sample of continental European firms. Political and governance factors are important for the going private decision. For example, Aguilera (2005) finds that corporate governance matters and director accountability varies, depending on the institutional setting and rule changes. Wright et al. (2016), for example, discuss the impact of Brexit on LBOs.

Owners are not the same. The time horizon of owners and investors affects investment decisions (Thanassoulis and Somekh, 2015) and voting practices (Stathopoulos and Voulgaris, 2016). Connelly, et al. (2010) claim that different types of shareholders might serve as an influential form of company governance. They suggest that corporate owners, on one hand, provide capital to the firm; yet, on the other hand, they are mostly interested in subsequently selling their shares in a takeover. Typically, a corporate takeover is a lucrative exit strategy for investors generating a high premium (Greenwood and Schor, 2009). The effect of institutional investors such as banks on firm corporate policies is inconclusive (Gorton and Schmid, 2000; Agarwal and Elston, 2001). Yuan et al. (2009) show that financial institutions play an important role in governance of listed companies in China. We expect greater agency problems when the firm is controlled by corporate or institutional shareholders and, therefore, greater potential gains from public to private transactions. Furthermore, corporate or institutional investors might be more likely to exercise an exit opportunity and obtain a lucrative premium through a buyout. Therefore, we predict that firms with a greater percentage of institutional or corporate owners are more likely to be targets in going private transactions.

Corporate and institutional investors are concentrated owners and, as such, are more likely to be blockholders. As a blockholder, a corporate or institutional investor would have an exacerbated incentive to exercise a buyout for the following reasons. Public firms have significant costs of disseminating information (Bharath and Dittmar, 2010). Merton (1987) shows that under imperfect information expected returns to investors decrease with the size of the investor base. Block ownership by outside investors is associated with concentrated monitoring and private benefits. Blockholders can exercise their power over management. Yet, concentrated ownership often leads to costly overmonitoring and a decline in managerial initiative (Burkart, et al. 1997; Pagano and Roell, 1998). Furthermore, blockholders can often exercise their power, which leads to wealth expropriation from minority shareholders; these private benefits of block ownership have been confirmed by Barclay and Holderness (1989, 1991, 1992) through evidence that blockholder trades are at a premium, thus implying private benefits of control. Blockholders may also benefit through production synergies associated with cross-ownership of other companies owned and controlled by the blockholders, and they make better use of those synergies without the costs of disseminating information in the ways required when the company is public. If the block ownership is associated with costly overmonitoring, a decline in managerial incentives, production synergies, and wealth expropriation, we would expect higher buyout probability to enable value creation through reducing agency costs and improvements in operating efficiency.

H1: *Corporate and institutional ownership increase the probability of a public to private transaction.*

H2: *Blockholdings of corporate and institutional ownership exacerbate the increase in the probability of a public to private transaction.*

Family firms, by contrast, have a substantially less pronounced separation of ownership and control. Family shareholders typically have tighter control over (or are a part of) the management team; as such, there is evidence that family owned firms have better performance and a lower cost of debt (Anderson and Reeb, 2003; Anderson, et al., 2003). Thus, companies owned by families are expected to have lower agency costs (Jensen and Meckling, 1976) and to run more efficiently.[6] As the potential for value creation associated with mitigating agency costs is less pronounced for buyouts of family firms, we expect family ownership to lower the probability of a public to private transaction. Ahlers et al. (2017) find that non-financial factors are particularly important among non-family firms in buyouts, and there is related evidence that innovation is valued less among family firms (Chang et al., 2010). Furthermore, there could be emotional ties associated with family ownership that reduce the likelihood of a buyout (Zellweger and Astrachan, 2008).

H3: *Family ownership decreases the probability of a public to private transaction.*

H4: *Blockholdings of family ownership exacerbate the decrease in the probability of a public to private transaction.*

4.3. Data

4.3.A. Sample Selection

We select a sample of worldwide public to private buyouts from the Zephyr database. We select all institutional and management buyouts where the public firm was a target in the buyout transaction and became private. We carefully check the delisting reason for each target firm and make sure that the delisting date is later than the buyout date. We include whole company buyouts and buildup strategies (i.e. where the transaction was completed in several stages). In the case of whole company buyouts, the entire firm is converted from a public to private company in a single transaction. In other words, whole company buyouts are those that are not done through a buildup strategy.

We construct the main measure of ownership using data from the Orbis database. The Orbis ownership database is a primary source for owner links around the world for around 7 million companies. We decided to use Zephyr as a source of buyout transactions, as it shares common identifiers with Orbis, and both databases are provided by one vendor—Bureau Van Dijk.

All financial information is primarily from Orbis, supplemented by Thomson Reuters. All financial data are from the last fiscal year end before the going private transaction. Our main sample contains 778 public to private transactions from 2002 to 2014 from 36 countries, including Australia, Belgium, Bulgaria, Canada, China, Denmark, Finland, France, Germany, Greece, Honk Kong, Hungary, India, Ireland, Israel Italy, Japan, Republic of Korea, Lithuania, Malaysia, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russian Federation, Singapore, South Africa, Spain, Sweden, the United Kingdom, and the United States of America.

We choose a control sample, as the distribution of buyouts is not random (Davis, et al. 2015). For each public to private firm, we find one matched firm based on country, industry, year, and revenue (Weir, et al., 2005; North, 2001; Klein and Zur, 2009). We summarize the sample decomposition in Table 4.1. In Column 2, we show all public to private deals in our sample; in Column 3, we show whole firm buyouts (buyouts that were not done through a buildup strategy); in Column 4, we show buyouts through buildup strategies; and, in Columns 5 and 6, we distinguish between management and institutional buyouts. In Panel A, we present composition by year. Looking at Table 4.1, we can see that public to private transactions occur in waves. With one wave around 2006-2007 and another wave around 2010-2011. So there is in fact some variability in the number of public to private transactions across time. We do not observe a clear increasing trend in the number of public to private transactions. There is a peak in buyouts in 2006-2007, reaching a number of 228 deals in 2007. In Panel B, we present composition by country. Buyouts through buildup strategies are common; yet, only in certain countries, with the majority of deals taking place in France, Germany, Italy, and the US. This might be related to strong shareholders' rights and the difficulty of buying the whole company. In Panel C, we present composition by industry. Most of the deals occur in the services and manufacturing sector.

[Insert Table 4.1 here]

4.3.B. Ownership Measures

We generate ownership measures based on the ownership data provided by Orbis. For each target firm going private, we extract information on its immediate shareholders. We then generate three types of shareholders: 1) INSTITUTION is equal to the percentage of ownership of institutional investors, including private equity, banks, venture capital, etc.; 2) CORPORATION is equal to the percentage of ownership of an industrial company; and 3) FAMILY is equal to the percentage of ownership of family.

We also generate the block ownership variables. We define block ownership when one type of shareholder holds more than 10% of the stock. We define three types of blockholders: 1) INSTITUTION_BLOCK, equal to one if the ownership of institutional investors is greater than 10%; 2) CORPORATION_BLOCK, equal to 1 if the percentage of ownership of the industrial company is greater than 10%; and 3) FAMILY_BLOCK, equal to one if the ownership of family is greater than 10%, and zero otherwise.

4.3.C. Other Controls

Although the main focus of our analysis is to analyze the relationship between ownership and public to private transactions, we also include other variables that are identified in the previous literature as determinants of buyout transactions. The theories of agency problems between the principal and agent of Jensen (1986) argue that firms with more free cash flow are more likely to be targets in buyout transactions (e.g., Halpern, Kieschnick, and Rotenberg,1999; Lehn and Poulsen, 1989). Financial leverage is important in many buyout transactions, as it shows the magnitude of the borrowing costs. Yet, it has been shown that buyout transaction can cause wealth expropriation from bondholders to shareholders (Asquith and Wizman, 1990). Growth opportunities are also related to the free cash flow hypothesis and debt level. Firms with low growth prospects might misuse the cash flows and invest in negative NPV projects. On the other hand, firms with excessive debt levels might underinvest and forgo positive NPV projects.

We, therefore, include the following control variables. First, we include target firm age (AGE), the age of the company in years. Second, we control for target firm total assets in the logarithm (ASSETS). Third, we include a return on assets (ROA) that proxies for profitability of the firm. Fourth, following Jensen (1986), we control for the misuse by entrenched managers of free cash flows (CASHFLOW). Fifth, we include the debt-to-asset ratio (LEVERAGE) that proxies for borrowing costs and wealth expropriation. Sixth, we control for the ratio of fixed assets to total assets (CAPINV). Finally, we include the market-to-book ratio (MB) to control for growth opportunities.

4.3.D. Country Characteristics

Investor protection has an important effect on firm governance (La Porta et al., 1998), we therefore include, as control variables, several measures that proxy for legal, institutional, and creditor rights. We control for creditor rights using an index developed by La Porta et al. (1998) and for legal origin an English legal region that is equal to 1, if a firm is incorporated in a country of English legal origin before going private, and zero otherwise. We also control for country market size using the natural log of GDP per capita of the country in which the firm is incorporated before going private.

4.4. Univariate Tests

In Table 4.2, we compare the going private sample with the control sample of matched firms that remained public. We first report summary statistics for the going private sample and then for firms that remained public. In the last two columns, we present the difference between means of two samples and t statistics. The statistically significant t-test suggests that going private firms are different in terms of ownership from firms that remained public. In particular, going private firms have a higher institutional and corporation ownership percentage, but a lower family ownership percentage.

[Insert Table 4.2 here]

We also present our results graphically. In Figure 4.1, we show that the trends for different types of ownership are relatively stable over time. However, one can see that the average FAMILY ownership is higher for the non-buyout sample than for the buyout sample. In contrast, the average CORPORATION and INSTITUTIONAL ownership is lower for the non-buyout sample than for the buyout sample. This is in line with our univariate tests. We observe similar trends in Figure 4.2, where we only present whole company buyouts. Subsequently, in Figure 4.3, we present buyouts based on a buildup strategy. The plot suggests that there is only a difference in FAMILY ownership that is higher for the non-buyout sample than for the buyout sample.

[Insert Figures 4.1 to 4.3 here]

Table 4.3 presents the correlations between variables. Institutional and corporate ownership are positively and significantly correlated with the going private probability. Family ownership is negatively and significantly correlated with the going private probability.

[Insert Table 4.3 here]

4.5. Multivariate Regressions

4.5.A. Ownership Structure

We first examine how different shareholder types affect the probability of going private. We focus on three types of shareholders: institution, family, and corporation. We aggregate percentages of shares held by all shareholders from each of these three types. For example, institutional ownership is the percentage of shares held by all institutional shareholders. In Table 4.4, we present the results of logit regressions. In Models 1 to 5, the dependent variable is equal to 1, if the target firm went private after a buyout transaction, and 0 otherwise. In all models, standard errors are clustered by industry (Petersen, 2009). We report average marginal effects with p-values below.

[Insert Table 4.4 here]

In Model 1, we present the results for the whole sample of going private transactions. The institutional and corporate ownership has a positive and significant effect on the probability of going private, consistent with H1, while the family ownership has a negative and significant effect on the probability of going private, consistent with H3. All three ownership variables are significant at the 1% level. The average marginal effect of the institutional ownership is 0.0032. The interpretation is that a one percent increase in intuitional ownership would increase the probability of going private by 0.32%. Similarly, one percentage increase in corporation ownership would increase the probability of going private by 0.23%. However, a one percent increase in family ownership would decrease that probability by 0.23%. The results are consistent with our predictions.

In Model 2, we present the results for a sample of targets that underwent a whole company buyout in one stage. We observe similar results. Corporate ownership has an even stronger effect. The probability of going private increases by 0.28% if the corporate ownership increases by 1%.

In Model 3, we present the results for the targets that went private in a buildup strategy, where the acquirer bought the target firm in several stages. In the case of a buildup strategy, only family ownership is a strong deterrent against going private buyouts. The probability of going private decreases by 0.60% if the family ownership increases by 1%. The other two types of ownership show no significant effect.

In Model 4, we present the results for management buyouts. The corporate ownership has a positive and significant effect (at the 10% level) on the probability of a management buyout.

In Model 5, we present the results for institutional buyouts. We show that corporate and institutional ownership is positively associated with an institutional buyout that results in going private, while family ownership is negatively associated with the probability of an institutional buyout. Again, all three are significant, and the effect magnitudes are very close to what we reported for the whole sample.

Many of the control variables are significant in Table 4.4. For example, we find that the probability of going private is higher for younger firms with lower profitability, higher free cash flows, higher leverage, and less fixed assets. We also find that the credit rights index increases the probability of whole company and institutional buyouts. These findings are consistent with

Cao, Cumming, Qian, and Wang (2015), who show that LBOs are facilitated by stronger creditor rights.

4.5.B. Ownership Block

Instead of using aggregated ownership percentages, we look at the ownership structure by using a dummy variable for each of the three shareholder types. For each type, the dummy equals 1, if the aggregate ownership is higher than 10% of the total shares. For example, an institution block is equal to 1, if the aggregate institution ownership in a firm is higher than 10%. This process allows us to compare firms closely held by a particular type of shareholders with those not held closely by the same type of shareholders.

In Table 4.5, we present the results for the effect of block ownership on the going-private decision. As seen previously, in Models 1 to 5, the dependent variable is equal to 1, if the firm went private as a result of a buyout transaction, and 0 otherwise. In all models, standard errors are clustered by industry. We report average marginal effects with p-values below.

[Insert Table 4.5 here]

Results here confirm our previous findings reported in Table 4.4. We show that if a firm is closely held by an institution or corporation, the probability of going private is higher, consistent with H2. However, if closely held by family, the probability of going private is lower, as expected, based on H4. In Model 1, for the whole sample, all three ownership variables are significant. The average marginal effect of the institution block is 0.1381, significant at the 1% level, and that of the corporation block is 0.1061, significant at the 5% level. The family block has a negative marginal effect of -0.1361, significant at the 1% level. On average, a firm closely held by institution (corporation) shareholders is 13.81% (10.61%) more likely to go private than a firm not closely held by institution (corporation) shareholders. A firm closely held by family shareholders is 13.61% less likely to go private than a firm not closely by family shareholders. Using both the whole firm buyout sample and the institutional buyout sample, we see consistent results.[7]

We find that block ownership is not related with the probability of going private in a buildup strategy. A family block is still a strong deterrent against going private in a management buyout, suggesting that firms with a strong family block have strong control over management.

4.5.C. Endogeneity of Ownership Structure

In this subsection, we discuss the potential endogeneity issue when analyzing the ownership and the decision to go private. The problem of endogeneity is quite common in international studies (Reeb, et al., 2012). However, while it is extremely unlikely that the going private decision determines the firm's ownership structure, the firm might have some unobservable characteristics that might determine both ownership structure and the decision to go-private. Although it is difficult to completely address the endogeneity problem, we try to mitigate the potential bias in the three following ways. First, the carefully chosen sample design already corrects for the endogeneity concerns, as we match firms that go private with a similar control sample of firms that remain public, based on country, industry, year, and sales (Weir, et al., 2005; North, 2001; Klein and Zur, 2009; Davis, et al., 2015). Second, in order to further alleviate these concerns, we perform an additional test, where we include country *x* year and industry *x* year fixed effects to capture omitted variables. Third, we instrument for the ownership structure and perform instrumental variable regression.

We test the robustness of our baseline results in Table 4.6. We replicate the results reported in Table 4.4 by adding country *x* year fixed effects in Panel A and by adding industry *x* year fixed effects in Panel B. The results reported in Table 4.6 with country *x* year and industry *x* year fixed effects support our baseline regressions. All effects remain similar to baseline findings in Table 4.4 in magnitude and statistical significance levels.

[Insert Table 4.6 here]

In Table 4.7, we present instrumental variable regressions. In Model 1 to 4, we present the results for the whole sample of going private transactions. The instrument for 1) INSTITUTION is an indicator variable that is equal to one, if the institution ownership is greater than the median largest industry ownership, and zero otherwise; 2) FAMILY is an indicator variable that is equal to one, if the family ownership is greater than the median largest industry ownership, and zero otherwise; and 3) CORPORATION is an indicator variable that is equal to one, if the corporation ownership is greater than the median largest industry ownership, and zero otherwise. The median industry ownership is calculated for the initial year of our sample. The median industry ownership is correlated with the firm's ownership structure but is unlikely to affect the buyout probability, except through the target's ownership structure. The first stage of our regressions (untabulated) suggests that instruments are valid. In Table 4.7, we present second stage instrumental variables regressions. All effects remain similar to previous findings in magnitude and statistical significance levels.

[Insert Table 4.7 here]

4.5.D. Additional analyses

Antidirector rights across countries might affect going private transactions in ways consistent with potential wealth expropriation of minority shareholders. Delisting may be undesirable for minority shareholders for at least two primary reasons. First, minority shareholders lose liquidity; and, second, transparency decreases due to fewer disclosure requirements. This implies that strong antidirector rights (measured using ADRI[6]) would deter whole company buyouts, while increasing the probability of build-up buyouts, where the acquirer buys the firm in several stages and delists it once it has majority votes. We tested this hypothesis (results not tabulated) and found some evidence that stronger antidirector rights increase the likelihood of going private in the case of a buildup strategy, while the effect on the probability of whole company buyouts was negative, albeit statistically insignificant. We also interacted an ADRI_D[7] variable with an ownership type (results not tabulated) and found that positive relationships between corporate ownership and buyout, and between institutional ownership and buildup type buyout, is mitigated when ADRI is higher than its mean. The interaction of ADRI with other ownership variables and for other types of buyouts did not result in statistically significant results.

The level of corruption in a country and the degree to which the less powerful members of a society accept and expect power to be distributed equally might also impact buyout probabilities. Hence, we considered models including the Corruption Perception Index (CPI[8]) and the Power Distance Index (PDI[9]) as control variables (results not tabulated), and found these variables to not have any effect on our main results.

The weak effect of ADRI, CPI, and PDI may be a result of these variables having very little variability over the sample period for any given country. We have also tried the interaction of ADRI_D, CPI_D[10] and PDI_D[11] with the ownership variables (results not tabulated). We find that the positive relationship between institutional ownership [corporate ownership] and buyout probability is mitigated when CPI [PDI] is higher than its mean. The other interaction terms did not show any significant results.

We analyzed interactions between ownership types and various proxies for cultural dimensions of the target country including Trust[12], Individualism[13], IDV[14], MAS[15], UAI[16], ITOWS[17], and IVR[18] (results not tabulated). The interaction of corporate ownership and Trust (only for Management buyouts); IDV (for all buyouts, whole firm buyouts, and institutional buyouts); MAS (for all buyouts, whole firm buyouts, and institutional buyouts); and IVR (for all buyouts and institutional buyouts) has a positive coefficient, indicating that these cultural variables increase the probability of a buyout when there is corporate ownership. We believe that future research can further investigate the effect of cultural dimension.

Finally, we tried standard industry fixed effects and country fixed effects regressions (without including any time fixed effects) and find that our results are unchanged to these alternative specifications (results not tabulated).

4.5.E. Limitations and Extensions

In this paper, we assess a link between ownership and going private. The stability in different types of ownership in the period from -10 years to -1 year, prior to going private, is suggestive that ownership is not endogenous to going private. Our instrumental variable analyses are consistent with this interpretation, and our regression analyses with country, industry, and year fixed effects confirm a link between ownership and going private. However, our sample does not offer a natural experiment nor a randomized test to provide further assessment of causality. Future work as other samples become available in different countries over different time periods might shed further light on this issue.

Also, further work could consider the performance implications of going private transactions for shareholders. Our cross-country legal analyses are suggestive of conflicts of interest between majority and minority shareholders. The extent of wealth expropriation and insider dealing, and other possible conflicts of interest, is worthy of further study.

4.6. Conclusion

In this paper, we examine the ownership structure before the public to private transaction. Based on data from 36 countries spanning 12 years, we find strong and consistent evidence that pre-going private ownership is characterized by higher institutional and corporate ownership. All these data suggest that buyout transactions are often motivated by reducing overmonitoring, agency problems, and improving management efficiency. We also find that family ownership (or block) is a strong deterrent against a going private buyout. This supports the predictions that family owned firms are run more efficiently[19]. Management buyouts are more likely when the firm is owned by a corporate investor. We also find that going private through a buildup strategy is less likely if the firm is owned by family, while management buyouts are more likely when the firm is owned by a corporate investor. Overall, the data are consistent with the view that corporate and institutional block ownership facilitates going private, while family ownership decreases the probability of going private. Overall, the data are consistent with the view that corporate and institutional block ownership facilitates going private, while family ownership decreases the probability of going private.

Furthermore, we highlight the role of creditor rights and legal conditions. We find some evidence that stronger creditor rights increase the probability of going private, especially in the case of whole company and institutional buyouts, while the legal conditions decrease the likelihood of going private for those buyout types.

Our study has some managerial implications as well. The composition of ownership is one of the most important factors for improving a firm's efficiency. Going private transactions imply, for minority shareholders, a lack of liquidity and a lack of transparency. Consequently, some dispositions could be better at integrating all shareholders (minority and majority). The study also highlights the role of the legal system in protecting shareholders.

Future research could examine whether the shareholders, particularly the minority shareholders, were treated differently depending on the ownership structure. Future research could also examine the real operating consequences on firms, including labor and productivity, conditional on the pre-going private ownership in different countries around the world. Future research could also study the reason why family ownership positively affects the efficiency of the going private transaction.

Figure 4.1. The dynamics of ownership over time (All Public to private deals)

This figure presents the dynamics of the average percentage in ownership in the months before the buyout and non-buyout deals.

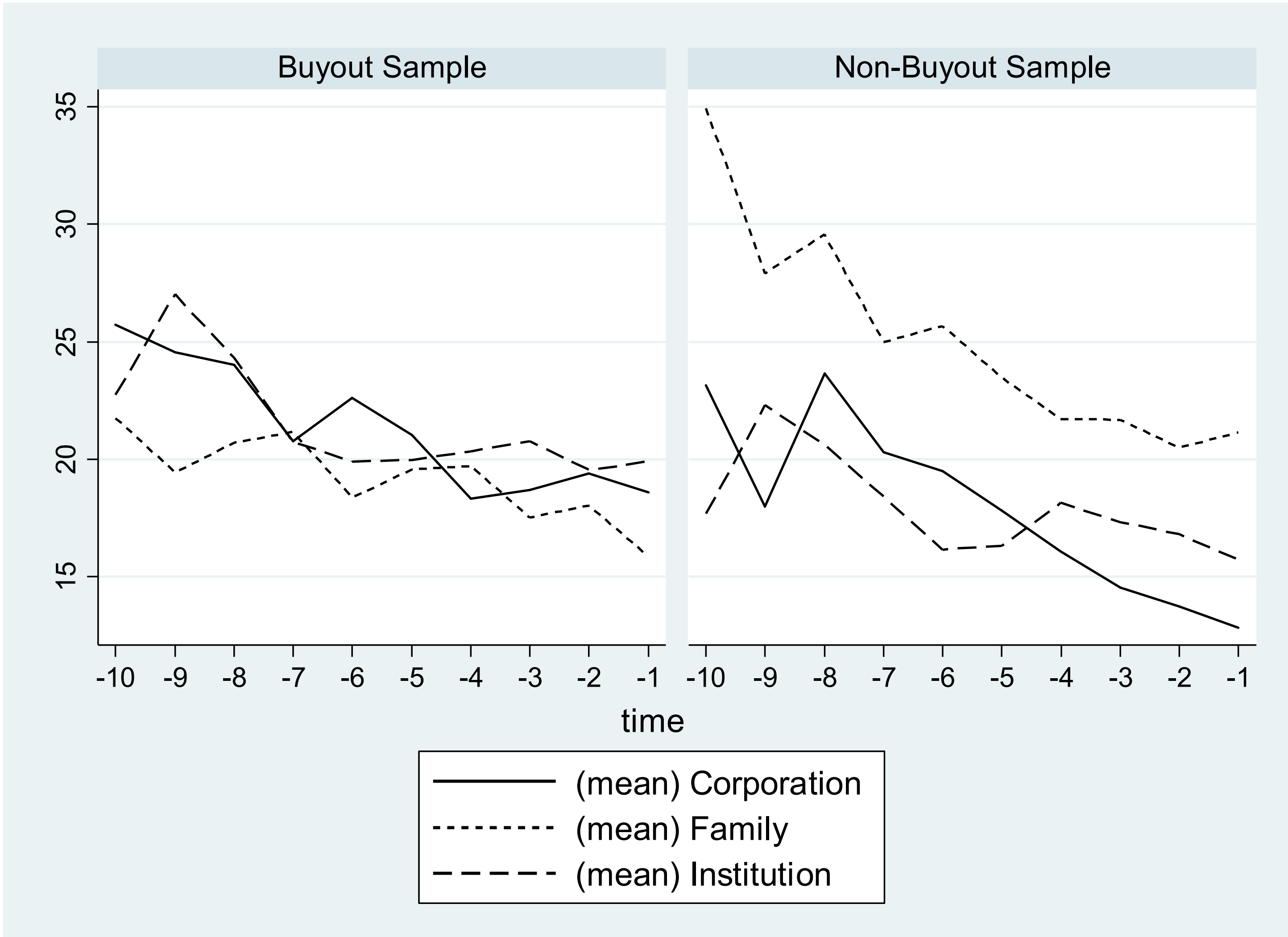


Figure 4.2. The dynamics of ownership over time (Whole firm buyout)

This figure presents the dynamics of average percentage ownership in the months before the buyout and non-buyout deals.

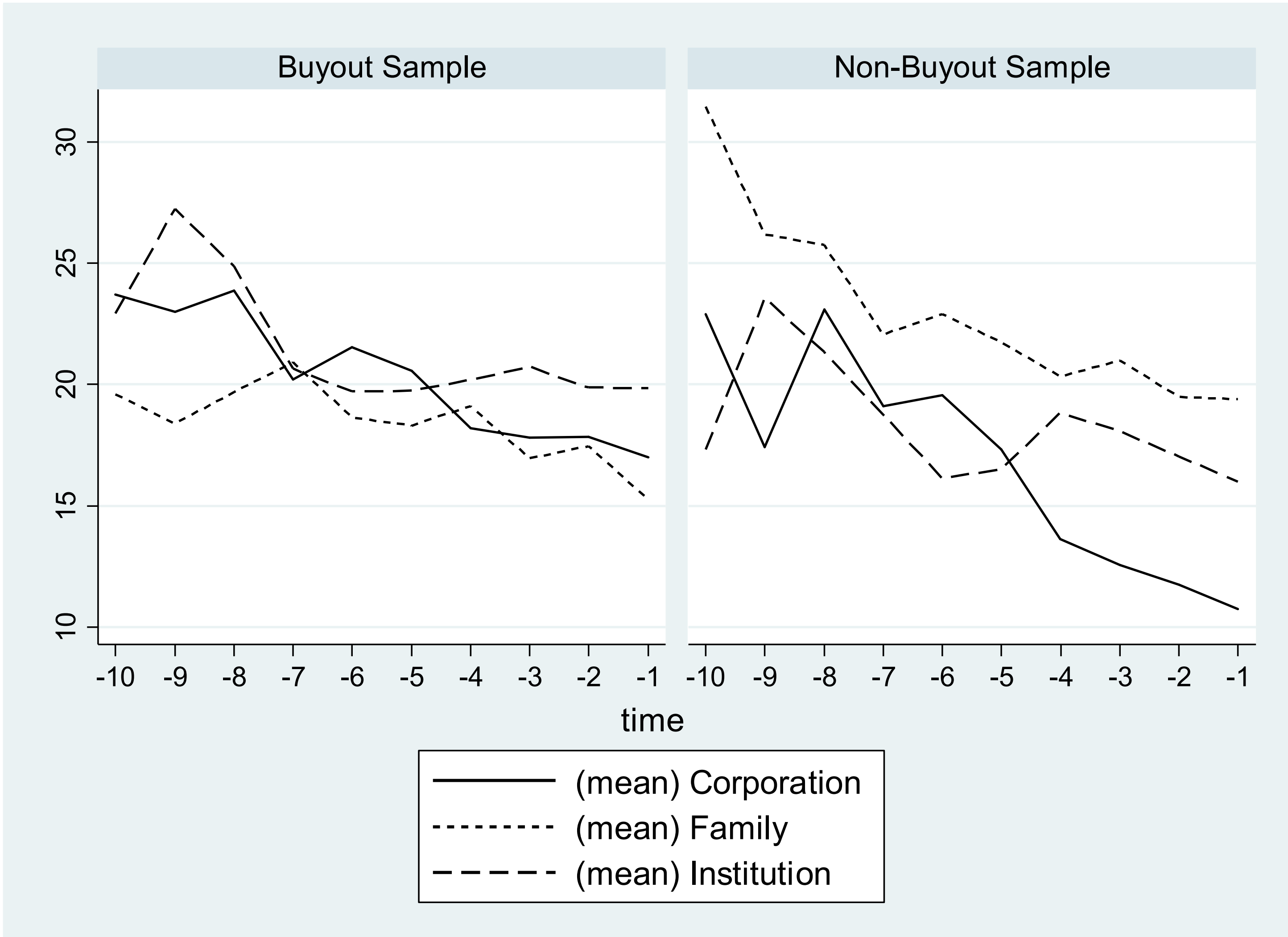


Figure 4.3. The dynamics of ownership over time (Buildup strategy)

This figure presents the dynamics of average percentage ownership in the months before the buyout and non-buyout deals.

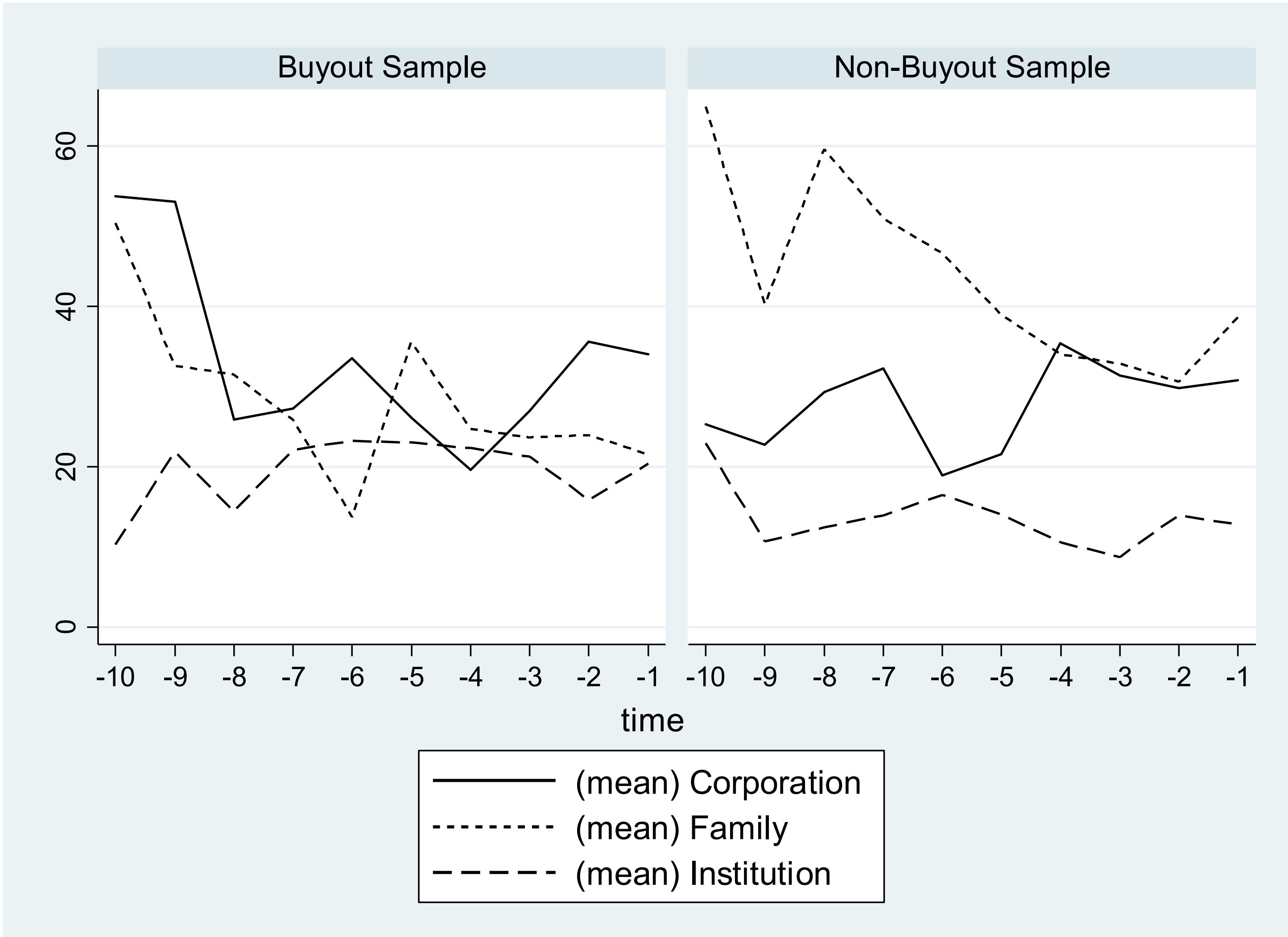


Table 4.1. Sample

The sample contains 778 Public to private transactions from 2002 to 2014 around the world, matched with 778 control firms based on country, industry, year, and sales. In Column 2, we present a sample composition for all Public to private buyouts. In Column 3, we present a sample composition for whole company buyouts. In Column 4, we present the firms that went private in buildup strategies. In Columns 5 and 6 ,we present firms that went private through institutional buyout and management buyout, respectively. We present sample decomposition by year in Panel A, by target firm country in Panel B, and by target firm industry in Panel C.

Panel A. Composition of sample by year

Year	All Public to private deals	Whole firm buyout	Buildup strategy	Management buyout	Institutional buyout
2002	10	6	4	0	10
2003	80	64	16	34	46
2004	92	74	18	10	82
2005	140	126	14	14	126
2006	202	182	20	14	188
2007	228	210	18	12	216
2008	118	106	12	18	100
2009	86	80	6	14	72
2010	138	128	10	14	124
2011	160	142	18	6	154
2012	114	108	6	12	102
2013	114	112	2	8	106
2014	74	72	2	4	70
Total	1556	1410	146	160	1396

Panel B. Composition of sample by country

Country	All Public to private deals	Whole firm buyout	Buildup strategy	Management buyout	Institutional buyout
AU(Australia)	32 (2.06%)	30 (2.13%)	2 (1.37%)	2 (1.25%)	30 (2.15%)
BE(Belgium)	2 (0.13%)	0 (0%)	2 (1.37%)	0 (0%)	2 (0.14%)
BG(Bulgaria)	2 (0.13%)	2 (0.14%)	0 (0%)	0 (0%)	2 (0.14%)
CA(Canada)	108 (6.94%)	108 (7.66%)	0 (0%)	8 (5%)	100 (7.16%)
CN(China)	2 (0.13%)	2 (0.14%)	0 (0%)	2 (1.25%)	0 (0%)
DE(Germany)	34 (2.19%)	18 (1.28%)	16 (10.96%)	0 (0%)	34 (2.44%)
DK(Denmark)	8 (0.51%)	6 (0.43%)	2 (1.37%)	0 (0%)	8 (0.57%)
ES(Spain)	8 (0.51%)	6 (0.43%)	2 (1.37%)	0 (0%)	8 (0.57%)
FI(Finland)	4 (0.26%)	2 (0.14%)	2 (1.37%)	0 (0%)	4 (0.29%)
FR(France)	74 (4.76%)	30 (2.13%)	44 (30.14%)	10 (6.25%)	64 (4.58%)
GB(UK)	212 (13.62%)	210 (14.89%)	2 (1.37%)	44 (27.5%)	168 (12.03%)
GR(Greece)	4 (0.26%)	0 (0%)	4 (2.74%)	0 (0%)	4 (0.29%)

HK(HongKong)	2 (0.13%)	2 (0.14%)	0 (0%)	0 (0%)	2 (0.14%)
HU(Hungary)	4 (0.26%)	2 (0.14%)	2 (1.37%)	0 (0%)	4 (0.29%)
IE(Ireland)	4 (0.26%)	4 (0.28%)	0 (0%)	4 (2.5%)	0 (0%)
IL(Israel)	2 (0.13%)	2 (0.14%)	0 (0%)	0 (0%)	2 (0.14%)
IN(India)	2 (0.13%)	0 (0%)	2 (1.37%)	0 (0%)	2 (0.14%)
IT(Italy)	16 (1.03%)	6 (0.43%)	10 (6.85%)	0 (0%)	16 (1.15%)
JP(Japan)	92 (5.91%)	86 (6.1%)	6 (4.11%)	42 (26.25%)	50 (3.58%)
KR(Korea)	2 (0.13%)	2 (0.14%)	0 (0%)	0 (0%)	2 (0.14%)
LT(Lithuania)	2 (0.13%)	2 (0.14%)	0 (0%)	0 (0%)	2 (0.14%)
MY(Malaysia)	10 (0.64%)	10 (0.71%)	0 (0%)	4 (2.5%)	6 (0.43%)
NL(Netherlands)	26 (1.67%)	20 (1.42%)	6 (4.11%)	4 (2.5%)	22 (1.58%)
NO(Norway)	18 (1.16%)	14 (0.99%)	4 (2.74%)	0 (0%)	18 (1.29%)
NZ(New Zealand)	4 (0.26%)	2 (0.14%)	2 (1.37%)	2 (1.25%)	2 (0.14%)
PH(Philippines)	2 (0.13%)	0 (0%)	2 (1.37%)	0 (0%)	2 (0.14%)
PL(Poland)	12 (0.77%)	6 (0.43%)	6 (4.11%)	0 (0%)	12 (0.86%)
PT(Portugal)	2 (0.13%)	2 (0.14%)	0 (0%)	2 (1.25%)	0 (0%)
RU(Russia)	2 (0.13%)	0 (0%)	2 (1.37%)	0 (0%)	2 (0.14%)
SE(Sweden)	18 (1.16%)	16 (1.13%)	2 (1.37%)	0 (0%)	18 (1.29%)
SG(Singapore)	26 (1.67%)	24 (1.7%)	2 (1.37%)	2 (1.25%)	24 (1.72%)
US(USA)	808 (51.93%)	784 (55.6%)	24 (16.44%)	34 (21.25%)	774 (55.44%)
ZA(South Africa)	12 (0.77%)	12 (0.85%)	0 (0%)	0 (0%)	12 (0.86%)
Total	1556 (100%)	1410 (100%)	146 (100%)	160 (100%)	1396 (100%)

Panel C. Composition of sample by industry

Industry	All Public to private deals	Whole firm buyout	Buildup strategy	Management buyout	Institutional buyout
Agriculture	2	2	0	0	2
Construction	18	16	2	2	16
Finance, Insurance	256	234	22	34	222
Manufacturing	404	352	52	42	362
Mining	28	26	2	2	26
Retail Trade	172	166	6	20	152
Services	490	448	42	36	454
Transportation	110	102	8	10	100
Wholesale Trade	76	64	12	14	62
Total	1556	1410	146	160	1396

Table 4.2. Univariate tests

	Going private **Firms**			**Control Sample**			**T-test for the Difference**	
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Diff in means	t-stat
Ownership variables								
INSTITUTION	778	19.4568	28.4473	778	11.9972	19.6090	-7.4596	-6.0221
FAMILY	778	3.4818	11.9795	778	5.3788	16.2718	1.8970	2.618658
CORPORATION	778	8.2785	23.1485	778	5.0733	16.1034	-3.2052	-3.17043
INSTITUTION_BLOCK	778	0.4370	0.4963	778	0.3111	0.4632	-0.1260	-5.17513
FAMILY_BLOCK	778	0.0835	0.2769	778	0.1272	0.3335	0.0437	2.812323
CORPORATION_BLOCK	778	0.1401	0.3473	778	0.1003	0.3005	-0.0398	-2.41981
Other variables								
AGE	778	24.0180	23.8733	778	26.7686	29.7786	2.7506	2.010198
ASSETS	778	5.4495	1.6659	778	5.4515	1.9316	0.0021	0.022584
ROA	778	0.1024	0.1866	778	0.1354	0.4493	0.0330	1.894442
CASHFLOW	778	-0.0044	0.1925	778	0.0216	0.3896	0.0260	1.66746
LEVERAGE	778	0.2622	0.3204	778	0.2339	0.4726	-0.0283	-1.38129
CAPINV	778	0.4938	0.4418	778	0.4340	0.7685	-0.0598	-1.88063
MB	778	7.7057	37.4491	778	5.8751	34.5855	-1.8306	-1.00165

Table 4.3. Correlations

	Buyout	Institution	Family	Corporation	Institution Block	Family Block	Corporation Block	AGE	ASSETS	ROA	CASH-FLOW	LEVE-RAGE	CAPINV	MB
BUYOUT	1.0000													
INSTITUTION	0.1510*	1.0000												
FAMILY	-0.0663*	-0.0681*	1.0000											
CORPORATION	0.0802*	-0.0957*	-0.0185	1.0000										
INSTITUTION BLOCK	0.1302*	0.7089*	-0.0380	-0.1306*	1.0000									
FAMILY BLOCK	-0.0712*	-0.0561*	0.8087*	-0.0154	-0.0101	1.0000								
CORPORATION BLOCK	0.0613*	-0.0512*	0.0185	0.8119*	-0.0856*	0.0276	1.0000							
AGE	-0.0509*	-0.0641*	-0.0677*	0.0250	-0.0769*	-0.0651*	0.0259	1.0000						
ASSETS	-0.0006	0.0314	-0.2177*	-0.0695*	0.0460	-0.2317*	-0.0542*	0.1469*	1.0000					
ROA	-0.0480	-0.0258	0.1524*	-0.0032	-0.0360	0.1195*	-0.0060	-0.0616*	-0.3510*	1.0000				
CASHFLOW	-0.0423	-0.0138	0.1414*	-0.0132	-0.0152	0.0986*	-0.0148	-0.0301	-0.2733*	0.9395*	1.0000			
LEVERAGE	0.0350	0.0486	0.1358*	0.0243	0.0052	0.0882*	0.0331	-0.0510*	-0.0039	0.5008*	0.4777*	1.0000		
CAPINV	0.0477	0.0012	0.0974*	0.0449	-0.0104	0.0522*	0.0502*	0.0417	-0.0685*	0.1131*	0.0489	0.1048*	1.0000	
MB	0.0254	-0.0149	0.1156*	0.0261	0.0003	0.0908*	0.0081	-0.0333	-0.1231*	0.1048*	0.0891*	0.0393	0.3163*	1.0000

Table 4.4. Ownership structure and going-private decision

This table presents logit regressions. The dependent variable in each regression is an indicator variable equal to one, if the firm goes private, and zero otherwise. The sample includes firms from 2002 to 2014. In Model 1, we present the results for the whole sample of going-private transactions. In Model 2, we present the results for a sample of targets that underwent a buyout of the whole company in one stage. In Model 3, we present the results for the targets that were acquired in a buildup strategy where the acquirer bought the target firm in several stages. In Model 4, we present the results for management buyouts. In Model 5, we present the results for institutional buyouts. All models include constant, industry and year fixed effects. Robust errors are clustered at industry level. We report the marginal effects with p-value in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels. See Appendix 1 for variable definitions.

	(1)	(2)	(3)	(4)	(5)
	All Public to private deals	Whole firm buyout	Buildup strategy	Management buyout	Institutional buyout
Ownership					
INSTITUTION	0.0032***	0.0033***	0.0033	0.0001	0.0034***
	(0.0000)	(0.0000)	(0.3963)	(0.9839)	(0.0000)
FAMILY	-0.0023***	-0.0018*	-0.0060*	-0.0011	-0.0024***
	(0.0019)	(0.0574)	(0.0646)	(0.7378)	(0.0056)
CORPORATION	0.0023***	0.0028***	-0.0011	0.0059**	0.0021***
	(0.0000)	(0.0000)	(0.6385)	(0.0113)	(0.0001)
Controls					
AGE	-0.0010*	-0.0009*	-0.0019*	-0.0006	-0.0012*
	(0.0649)	(0.0864)	(0.0790)	(0.6267)	(0.0545)
ASSETS	-0.0113*	-0.0107	-0.0334	-0.0022	-0.0095
	(0.0745)	(0.1173)	(0.2229)	(0.9443)	(0.1942)
ROA	-0.2970***	-0.2682***	-0.5571	-0.1835	-0.3370***
	(0.0000)	(0.0001)	(0.3857)	(0.5634)	(0.0045)
CASHFLOW	0.1420***	0.1061*	0.4132	0.1133	0.1868***
	(0.0000)	(0.0667)	(0.2993)	(0.7922)	(0.0004)
LEVERAGE	0.1011**	0.1054	0.0666	0.0586	0.1009
	(0.0368)	(0.1086)	(0.4035)	(0.4711)	(0.1050)
CAPINV	0.0487	0.0411	0.1289	0.2558**	0.0555*
	(0.2027)	(0.2245)	(0.4918)	(0.0286)	(0.0770)
MB	0.0003	0.0003	-0.0022	0.0038***	-0.0002
	(0.5755)	(0.5213)	(0.6786)	(0.0034)	(0.6594)
GDPCAPITA	0.0079	0.0146	0.0106	0.0682	0.0025
	(0.5036)	(0.5652)	(0.7895)	(0.2888)	(0.8568)
CREDITOR_INDEX	0.0056	0.0075*	0.0076	0.0053	0.0055
	(0.1242)	(0.0610)	(0.6272)	(0.6746)	(0.2262)
LEGAL_UK	-0.0148*	-0.0051	-0.0645**	0.0469	-0.0162*
	(0.0684)	(0.6618)	(0.0470)	(0.2452)	(0.0546)
N	1556	1410	146	160	1396
PSEUDO R-SQ	0.0362	0.0379	0.0664	0.0690	0.0395
LOG LIK.	-1039.4481	-940.3442	-94.4810	-103.2515	-929.3679

Table 4.5. Block ownership and going-private decision

This table presents logit regressions. The dependent variable in each regression is an indicator variable equal to one, if the firm goes private, and zero otherwise. The sample includes firms from 2002 to 2014. In Model 1, we present the results for the whole sample of going-private transactions. In Model 2, we present the results for a sample of targets that underwent a buyout of the whole company in one stage. In Model 3, we present the results for the targets that were acquired in a buildup strategy where the acquirer bought the target firm in several stages. In Model 4, we present the results for management buyouts. In Model 5, we present the results for institutional buyouts. All models include constant, industry and year fixed effects. Robust errors are clustered at industry level. We report the marginal effects with p-value in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels. See Appendix 1 for variable definitions.

	(1)	(2)	(3)	(4)	(5)
	All Public to private deals	Whole firm buyout	Buildup strategy	Management buyout	Institutional buyout
Ownership					
INSTITUTION BLOCK	0.1381***	0.1355***	0.2312	0.0260	0.1466***
	(0.0001)	(0.0001)	(0.1696)	(0.7923)	(0.0005)
FAMILY BLOCK	-0.1361***	-0.1256***	-0.2531	-0.1818*	-0.1353***
	(0.0000)	(0.0035)	(0.1783)	(0.0801)	(0.0000)
CORPORATION BLOCK	0.1061**	0.1301***	-0.0512	0.2304*	0.0965**
	(0.0107)	(0.0011)	(0.7921)	(0.0512)	(0.0484)
Controls					
AGE	-0.0010*	-0.0009*	-0.0025**	-0.0004	-0.0012**
	(0.0551)	(0.0772)	(0.0207)	(0.7101)	(0.0479)
ASSETS	-0.0137**	-0.0140**	-0.0233	-0.0175	-0.0113*
	(0.0163)	(0.0232)	(0.2582)	(0.5748)	(0.0641)
ROA	-0.2891***	-0.2634***	-0.5521	-0.2638	-0.3181***
	(0.0000)	(0.0000)	(0.4228)	(0.4351)	(0.0007)
CASHFLOW	0.1232***	0.0866	0.4559	0.1392	0.1584***
	(0.0000)	(0.1548)	(0.2676)	(0.7768)	(0.0001)
LEVERAGE	0.1148**	0.1233*	0.0324	0.0515	0.1161*
	(0.0139)	(0.0547)	(0.7146)	(0.4935)	(0.0514)
CAPINV	0.0482	0.0418	0.1457	0.2461*	0.0542*
	(0.2190)	(0.2253)	(0.4508)	(0.0529)	(0.0815)
MB	0.0002	0.0003	-0.0040	0.0039***	-0.0002
	(0.5733)	(0.4819)	(0.3694)	(0.0038)	(0.6702)
GDPCAPITA	0.0035	0.0115	-0.0013	0.1027	-0.0042
	(0.7035)	(0.5214)	(0.9740)	(0.1343)	(0.7083)
CREDITOR_INDEX	0.0066**	0.0076*	0.0090	0.0020	0.0067*
	(0.0265)	(0.0614)	(0.4020)	(0.8923)	(0.0625)
LEGAL_UK	-0.0214*	-0.0124	-0.0733	0.0332	-0.0256*
	(0.0645)	(0.3071)	(0.1540)	(0.2933)	(0.0603)
N	1556	1410	146	160	1396
PSEUDO R-SQ	0.0311	0.0315	0.0703	0.0666	0.0330
LOG LIK.	-1044.9606	-946.5941	-94.0864	-103.5184	-935.7423

Table 4.6. Robustness: Country *x* year and industry *x* year fixed effects

This table presents logit regressions. The dependent variable in each regression is an indicator variable equal to one, if the firm goes private, and zero otherwise. The sample includes firms from 2002 to 2014. In Model 1, we present the results for the whole sample of going-private transactions. In Model 2, we present the results for a sample of targets that underwent a buyout of the whole company in one stage. In Model 3, we present the results for the targets that were acquired in a buildup strategy where the acquirer bought the target firm in several stages. In Model 4, we present the results for management buyouts. In Model 5, we present the results for institutional buyouts. All models include constant, controls, industry and year fixed effects. Robust errors are clustered at industry level. We report the marginal effects with p-value in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels. See Appendix 1 for variable definitions.

	(1)	(2)	(3)	(4)	(5)
	All Public to private deals	Whole firm buyout	Buildup strategy	Management buyout	Institutional buyout
Panel A. Country *x* year fixed effects					
Ownership					
Institution	0.0037***	0.0038***	0.0040	-0.0009	0.0039***
	(0.0000)	(0.0000)	(0.5181)	(0.7926)	(0.0000)
Family	-0.0025***	-0.0019*	-0.0090*	-0.0015	-0.0026***
	(0.0020)	(0.0575)	(0.0643)	(0.6833)	(0.0076)
Corporation	0.0029***	0.0036***	-0.0017	0.0122*	0.0027***
	(0.0000)	(0.0000)	(0.6102)	(0.0551)	(0.0000)
N	1556	1410	146	160	1396
PSEUDO R-SQ	0.0419	0.0438	0.0910	0.1182	0.0455
LOG LIK.	1033.3853	-934.5384	-91.9922	-97.7920	-923.5916
Panel B. Industry x year fixed effects					
Ownership					
Institution	0.0034***	0.0035***	0.0048	-0.0002	0.0037***
	(0.0000)	(0.0000)	(0.2987)	(0.9485)	(0.0000)
Family	-0.0025***	-0.0018*	-0.0076**	-0.0021	-0.0025***
	(0.0022)	(0.0742)	(0.0342)	(0.5857)	(0.0080)
Corporation	0.0023***	0.0029***	-0.0011	0.0090***	0.0021***
	(0.0000)	(0.0000)	(0.7180)	(0.0081)	(0.0001)
N	1556	1410	146	160	1396
PSEUDO R-SQ	0.0382	0.0399	0.0844	0.0874	0.0423
LOG LIK.	1037.3032	-938.3024	-92.6621	-101.2137	-926.6817

Table 4.7. Robustness: Instrumental Variable (IV) estimation

This table presents instrumental variable regressions. The dependent variable in each regression is an indicator variable equal to one, if the firm goes private, and zero otherwise. The sample includes firms from 2002 to 2014. In Models 1 to 4,we present the results for the whole sample of going-private transactions. The instrument for 1) INSTITUTION is an indicator variable that equals to one, if the institution ownership is greater than the median largest industry ownership, and zero otherwise; 2) FAMILY is an indicator variable that equals to one, if the family ownership is greater than the median largest industry ownership, and zero otherwise; and 3) CORPORATION is an indicator variable that equals to one, if the corporation ownership is greater than the median largest industry ownership, and zero otherwise. All models include constant, controls, industry, and year fixed effects. Robust errors are clustered at industry level. We report the marginal effects with p-value in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels. See Appendix 1 for variable definitions.

	(1)	(2)	(3)	(4)
Ownership				
INSTITUTION	0.0030***			0.0030***
	(0.0000)			(0.0000)
FAMILY		-0.0025***		-0.0020**
		(0.0053)		(0.0458)
CORPORATION			0.0015**	0.0017***
			(0.0291)	(0.0061)
Controls				
AGE	-0.0010*	-0.0012**	-0.0011**	-0.0010*
	(0.0988)	(0.0241)	(0.0361)	(0.0678)
ASSETS	-0.0084	-0.0131***	-0.0080	-0.0108**
	(0.1534)	(0.0069)	(0.1584)	(0.0257)
ROA	-0.2940***	-0.3329***	-0.3221***	-0.2958***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CASHFLOW	0.1367***	0.1662***	0.1540***	0.1429***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LEVERAGE	0.1024**	0.1210**	0.1105**	0.1031**
	(0.0412)	(0.0110)	(0.0154)	(0.0328)
CAPINV	0.0508	0.0529	0.0491	0.0495
	(0.2844)	(0.2159)	(0.2681)	(0.2279)
MB	0.0002	0.0003	0.0002	0.0003
	(0.6258)	(0.5223)	(0.7101)	(0.5566)
GDPCAPITA	-0.0055	-0.0034	0.0060	0.0051
	(0.3307)	(0.4570)	(0.3493)	(0.6000)
CREDITOR_INDEX	0.0068**	0.0016	0.0033	0.0056
	(0.0409)	(0.4542)	(0.1006)	(0.1503)
LEGAL_UK	-0.0252***	-0.0138	-0.0066	-0.0173
	(0.0076)	(0.2409)	(0.6241)	(0.1386)
N	1556	1556	1556	1556
PSEUDO R-SQ	0.0207	0.0133	0.0131	0.0250
LOG LIK.	-1056.1931	-1064.2134	-1064.4382	-1051.5761

Appendix 4.1. Variables definitions

Variable Name	Definition
Dependent Variable	
INSTITUTIONAL BUYOUT	An indicator variable equal to one, if the institution ownership is greater than the median largest industry ownership, and zero otherwise; "This is an acquisition where a Private Equity firm has taken a 50% stake or more in the Target company, or is the parent of the acquirer. The acquisition often takes place through a 'new company' (newco) or an acquisition vehicle. Often the target company's management will take a small stake. If the buy-out is for less than 100 per cent of the target company, the deal is coded as IBO X%. Many deals described in the media as MBOs are coded on Zephyr as IBOs due to the fact that the management team did NOT take a majority stake in the target. There are very few occasions when venture capital may be inserted instead of private equity as the financing method. This would only occur when an early-stage company raises development capital funding, and the investors achieve a majority stake." [Zephyr Definition]
MANAGEMENT BUYOUT	An indicator variable equal to one, [????]. "All or some of the existing management of the company buys at least 50% of the company from its existing owners. A private equity company is often brought in to aid the purchase through provision of equity funding. A 'new company' (newco) is normally formed by the management team specifically to purchase the target. The acquirer company would also show 'MBO Team' unless the name of the newco is known. If the name of the newco has been released, this company would be entered as the acquirer. If the Private Equity firm backing the deal takes a majority stake in the target, the deal is not defined as an MBO and would be coded as an IBO."
WHOLE COMPANY BUYOUT	An indicator variable equal to one, if in the public-to-private buyout transaction acquirer has taken a 100% stake in the target company, and zero otherwise
BUILDUP BUYOUT	An indicator variable equal to one, if the public-to-private buyout transaction was completed in several stages, and zero otherwise
Ownership	
INSTITUTION	The percentage ownership of private equity or bank
FAMILY	The percentage ownership of family
CORPORATION	The percentage ownership of industrial company
INSTITUTION_BLOCK	An indicator variable equal to one, if ownership of private equity or bank is greater than 10%, and zero otherwise
FAMILY_BLOCK	An indicator variable equal to one, if ownership of family is greater than 10%, and zero otherwise
CORPORATION_BLOCK	An indicator variable equal to one, if percentage ownership of industrial company is greater than 10%, and zero otherwise
Controls	
AGE	The natural logarithm of the company age in years
ASSETS	The natural logarithm of total assets
ROA	Return on assets
CASHFLOW	Operating income minus capital investment minus change in net working capital scaled by total assets
LEVERAGE	The ratio of total debt to total assets
CAPINV	The ratio of fixed assets to total assets
MB	The firm's market-to-book
GDPCAPITA	Gross national income per capita [World Development Indicators]
LEGAL_UK	An indicator variable equal to one, if the firm is incorporated in a country of English legal origin before going private, and zero otherwise [La Porta et al. (1998)]

CREDITOR_INDEX	Creditor rights index from La Porta et al. (1998). A score of one is assigned when each of the following rights of secured lenders are defined in laws and regulations: First, there are restrictions, such as creditor consent or minimum dividends, for a debtor to file for reorganization. Second, secured creditors are able to seize their collateral after the reorganization petition is approved, i.e., there is no automatic stay or asset freeze. Third, secured creditors are paid first out of the proceeds of liquidating a bankrupt firm, as opposed to other creditors such as government or workers. Finally, if management does not retain administration of its property pending the resolution of the reorganization. The index ranges from 0 (weak creditor rights) to 4 (strong creditor rights) and is constructed as at January for every year from 1978 to 2003. [La Porta (1998)]

Chapter 5

Concluding Remarks

This dissertation contributes to our knowledge of the interaction between Finance and Innovation and to our understanding of Public to Private transactions, and the effect of these transactions on target firms. This dissertation provides insight into the effect of stock market manipulation and public to private buyout transactions on both the quantity and quality of innovation. In addition, we gain a deeper understanding of how ownership structure plays an important role in public to private buyout transactions.

In the first essay, we study the effect of suspected market manipulation on innovation measures such as the number of patents and number of patent citations. We consider two types of suspected manipulation cases – End of Day manipulation and Information leakage. We find that firms that have experienced End of day manipulation more than once, subsequently produce fewer patents and these patents are cited fewer times. This implies a strong negative impact on the innovativeness of these firms. On the other hands, firms that have experienced information leakage do not reduce their patents or citations, and in certain cases, we find a positive effect of this type of manipulation on innovation.

In the second essay, we investigate the effect of public to private transaction on the innovation activity of target firms. We find that after a public to private buyout, the target firms have fewer number of patents as well as fewer number of citations. They also reduce the number of radical patents and lower their innovation efficiency. The negative effects on innovation is more pronounced for institutional buyouts, and for the post-2006 period.

In the third essay, we examine how ownership structure has an impact on the public to private transactions. We find strong evidence that before going private, target companies are characterized by higher institutional and corporate ownership. Family ownership reduces the likelihood of going private transactions. We also find that Management Buyouts are more likely in the case of a corporate ownership. In addition, we also find that strong creditor rights are associated with an increased probability of going private buyout, while legal conditions decrease the probability of going private.

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NOTES

[1] Not all buyouts are going private transactions, and likewise, not all buyouts or going private transactions involve private equity sponsors. In this paper, we use the term 'buyout' to refer to public to private buyout transactions only, and consider both private-equity and non-private equity sponsored buyouts.

[2] Ben Stein, "On Buyouts, There Ought to Be a Law" The New York Times (September 3, 2006), at http://www.nytimes.com/2006/09/03/business/yourmoney/03every.html?ex=1314936000&en=6679077c5af5c4a6&ei=5088&partner=rssnyt&emc=rss

[3] "The uneasy crown," The Economist (February 8, 2007) http://www.economist.com/node/8663441

[4] http://en.wikipedia.org/wiki/Locust_(finance)

[5] For example, in a recent legal dispute involving Protective Products of America (PPA), PPA allegedly did not disclose material information about a $300 million contract award and was subsequently delisted and then put into bankruptcy. In bankruptcy, PPA was sold to a new company created by many of the prior managers of PPA. With the help of a PE fund, the new company bought PPA's assets in bankruptcy for roughly $10 million. Shortly thereafter, the managers of new announced the $300 million contract award.

[6] The Antidirector Rights Index (ADRI) is formed by adding one when: (1) the country allows shareholders to mail their proxy vote, (2) shareholders are not required to deposit their shares prior to the General Shareholders' Meeting, (3) cumulative voting or proportional representation of minorities on the board of directors is allowed, (4) an oppressed minorities mechanism is in place, (5) the minimum percentage of share capital that entitles a shareholder to call for an extraordinary Shareholders' Meeting is less than or equal to 10 percent the sample median, or (6) when shareholders have pre-emptive rights that can only be waived by a shareholders meeting.

[7] ADRI_D is a dummy variable that is equal to one, if the ADRI is higher than the mean of ADRI, and zero otherwise.

[8] The Corruption Perceptions Index (CPI) scores and ranks countries/territories based on how corrupt a country's public sector is perceived to be [Transparency International]

[9] The Power Distance Index (PDI) measures the degree to which the less powerful members of a society accept and expect that power is distributed unequally [http://geert-hofstede.com/]

[10] CPI_D is a dummy variable that is equal to one, if the CPI is higher than the mean of CPI, and zero otherwise.

[11] PDI_D is a dummy variable that is equal to one, if the PDI is higher than the mean of PDI, and zero otherwise.

[12] Trust is a dummy variable equal to one, if the trust is higher than the mean, and zero otherwise. Trust is an average answer to the following question: "Generally speaking, would you say that (1) "Most people can be trusted." Or, (2) "Most people need to be very careful."

[13] Individualism is a dummy variable equal to one, if the individualism is higher than the mean, and zero otherwise. Individualism is an average answer to the following question: "Incomes should be more equal." Or, "We need larger income differences as incentives for individual effort."

[14] IDV is a dummy variable equal to one, if the IDV is higher than the mean, and zero otherwise. IDV is the Individualism versus Collectivism of the respective target country (see http://geerthofstede.com/national-culture.html).

[15] MAS is a dummy variable equal to one, if the MAS is higher than the mean, and zero otherwise. MAS is the Masculinity versus Femininity of the respective target country (see http://geerthofstede.com/national-culture.html).

[16] UAI is a dummy variable equal to one, if the UAI is higher than the mean, and zero otherwise. UAI is the Uncertainty Avoidance Index of the respective country target country (see http://geerthofstede.com/national-culture.html).

[17] ITOWS is a dummy variable equal to one, if the ITOWS is higher than the mean, and zero otherwise. ITOWS is Long -Term Orientation versus Short-Term Normative Orientation of the respective target country (see http://geert-hofstede.com/nationalculture.html).

[18] IVR is a dummy variable equal to one, if the IVR is higher than the mean, and zero otherwise. IVR is the Indulgence versus Restraint of the respective target country (see http://geert-hofstede.com/nationalculture.html).

[19] Westhead and Cowling (1997) study the performance between family and non-family unquoted companies in the UK. They find that family companies are more interested in non-financial objectives than non-family companies. Daily and Dollinger (1992) and Neubauer and Lank (1998) find that family firms have superior performance to non-family firms. Ganderrio (1999) found that family firms have a higher level of ROE and are financially stronger than non-family firms. Anderson and Reeb (2002) show that family ownership is prevalent and substantially more profitable and more valuable than non-family ownership.

[20] In untabulated analysis, we checked whether our results are robust to the definition of the block ownership of 5% and 20%. The results remain unchanged.