ESSAYS ON FINANCE AND INNOVATION

A Thesis
Presented to
The Academic Faculty

by

Steven Chong Xiao

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
Scheller College of Business

Georgia Institute of Technology
December 2014

ESSAYS ON FINANCE AND INNOVATION

Approved by:

Professor Sudheer Chava,
Committee Chair
Scheller College of Business
Georgia Institute of Technology

Professor Vikram Nanda, Advisor
Rutgers Business School
Rutgers University

Professor Cheol S. Eun
Scheller College of Business
Georgia Institute of Technology

Professor Narayanan Jayaraman
Scheller College of Business
Georgia Institute of Technology

Professor Nishant Dass
Scheller College of Business
Georgia Institute of Technology

Date Approved: 31 October 2014

To Serena for your love and support.

ACKNOWLEDGEMENTS

I would like to use this opportunity to express my gratitude to everyone who supported me throughout the course of my Ph.D. study. A special thanks to my advisors, Prof. Vikram Nanda and Prof. Sudheer Chava, who have been influential mentors for me with their immense knowledge and unwavering support. I am grateful to my committee members, Prof. Cheol Eun, Prof. Narayanan Jayaraman, and Prof. Nishant Dass, without their invaluable advice and encouragement the dissertation would not have been possible.

I would like to thank Prof. Jonathan Clarke and Prof. Chayawat Ornthanalai for their guidance on writing my very first research paper. I would also like to thank Prof. Qinghai Wang for his advice and support that brought me into the program and all the stimulating suggestions throughout my study. I am thankful to all the other faculty members for their role in creating a supportive environment for the students. My gratitude also goes to Kyuseok Lee, Rohan Ganduri, Ji (Jay) Zhou, Youngmin Choi, and all the other fellow Ph.D. students, for the stimulating discussions and all the fun we had the past five years.

I am greatly indebted to my parents for their faith in me and the sacrifices they have made that allowed me to pursue my academic career. Lastly, I would like to express my deepest appreciation to my wife Serena for the love, patience, and companionship. I dedicate this dissertation to her.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

This thesis investigates the impact of finance on technological innovation. In the first essay we study the causal relation between informativeness of stock prices and innovative efficiency. Using mutual fund flow-driven price pressure as an exogenous shock, we show that impairment of stock price efficiency diminishes innovative efficiency. In the year following the price-pressure shock, patents per R&D dollar drop by 4.7%, while citations are 26.2% lower. Consistent with market feedback, stock mispricing has a greater effect on innovative efficiency when there is less information available from other sources, such as insider information or peers' stock prices. We do not find evidence supporting alternative explanations such as the endogeneity of mutual fund trading, financing effect, managerial incentive, or shareholder short-termism. Overall, our findings show that stock markets improve real efficiency by providing useful market feedback.

The second essay examines the implication of intellectual property protection (IP) to equity financing. Firms can protect IP by either keeping their inventions secret or seeking patent protection and disclosing the inventions. We expect the relative protection conferred by the methods to affect the choice between secrecy and patenting. Further, we expect the manner of IP protection to affect the information released by firms and, hence, their stock liquidity and cost of equity capital. For our empirical analysis, we rely on the exogenous passage of state-level statutes that strengthened trade secret protection. We show that stronger trade-secret protection increased opaqueness and reduced stock liquidity. Firms that raised equity capital after the enactment of trade secret statutes experienced more negative stock market reactions.

By contrast, the implementation of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS), that strengthened patent protection, improved the transparency and stock liquidity of patenting firms. After TRIPS the stock market reaction to equity offering by these firms was also less negative. Our findings suggest that stronger patent protection encourages more information disclosure and reduces financing frictions, while stronger secrecy protection induces opaqueness and makes equity financing more difficult.

In the third essay, we show that corporate investment in R&D declines sharply following a financial-covenant violation, wherein creditors can use the threat of accelerating the loan to press for changes in firm policies. The reduction in R&D is more severe in firms with low R&D efficiency i.e., when firm R&D is less productive in terms of ROA and delivers fewer patents and citations. It is striking that, despite decrease in R&D, covenant-violating firms do not suffer a drop in innovative output (patents and citations-to-patents). These results highlight that lenders are judicious in exercising their control rights after covenant violations and suggest that bank financing can be a viable source of financing for innovative firms.

CHAPTER I

DOES PRICE EFFICIENCY AFFECT REAL EFFICIENCY? EVIDENCE FROM INNOVATIVE ACTIVITIES

1.1 Introduction

It is generally believed that efficient financial market promotes real efficiency. Primarily, stock prices facilitate resource allocation by affecting firms' financing. Efficient markets, by accurately reflecting the value of firms' investment opportunity, ensure firms that have profitable investment projects have access to the needed capital. Moreover, stock markets may serve as a means of aggregating investors' information and providing managers with *feedback* that guides their investment decisions (Dow and Gorton, 1997). An efficient secondary stock markets can also help mitigate agency problems by rendering stock-based incentive contracts more effective (Holmström and Tirole, 1993).

In the empirical literature, a number of studies examine how the secondary stock markets affect real decision making and, hence, real efficiency. These studies typically focus on the impact of secondary stock market on firms' actions, such as financing and investment decisions.[1] However, direct empirical evidence linking financial market efficiency to real efficiency is still lacking. In this paper, we aim to address this issue and examine the empirical relation between price efficiency and real efficiency.

To study the long term impact of price efficiency, we focus on firms' R&D investment. Technological innovations have been recognized as a critical driver of economic

[1] e.g., See Baker, Stein, and Wurgler, 2003; Chen, Goldstein, and Jiang, 2006; Hau and Lai, 2013, Gao and Lou, 2013; Grullon, Michenaud, and Weston, 2014; etc.;

growth (Solow, 1957). As Baumol (2001) has pointed out, much of the technological innovation is contributed by established, public corporations. Meanwhile, there has been a debate as to whether stock market facilitate or hinder innovative activities. On the negative side, stock markets are sometimes blamed for inducing myopic behavior on the part of managers, discouraging longer-term investment, such as in R&D (Stein, 1988). A more positive view, however, is that the stock market can recognize the value of R&D investment by aggregating the information from a large number of investors (Rajan and Zingales, 2003). Therefore, it is not as yet fully understood whether stock market efficiency contributes to the efficiency of innovative activities.

We measure innovative efficiency by estimating the empirical relation between R&D investment and subsequent innovation output proxied by the number of patent applications and the future citations (Hirshleifer, Hsu, and Li, 2012). As R&D and patents reflect innovation input and output, their relation provides a direct measure of the efficiency of innovative activities compared with other more general measures of performance such as ROA, which may be influenced by many factors. Our identification strategy is to exploit an exogenous shock that induces stock price *inefficiency*. Specifically, we examine the impact of exogenous stock mispricing caused by mutual fund flow-driven price pressure (Coval and Stafford, 2007). Coval and Stafford (2007) find that mutual funds that increase (decrease) existing positions because of a large inflow (outflow) create price pressure in their overlapping holdings. Stocks under such pressure experience a temporary change in price that is reversed over time, which is an indication of mispricing. The exogeneity assumption can be justified on the grounds that such price pressure is driven by funding liquidity and is not related to the fundamentals of the firm.

We find that stock mispricing caused by mutual fund pressure adversely impacts future innovative efficiency. Based on our estimation, the same amount of R&D leads to 4.7% lower number of patent applications and 26.2% lower number of citations for these patents in the year after stock mispricing caused by mutual fund fire sales or purchases in a quarter. Moreover, our findings cannot be explained by the endogeneity of mutual fund pressure since both stock over-pricing and under-pricing lead to lower innovative efficiency.

We explore several potential mechanisms that may explain the link between price efficiency and innovative efficiency. Our first hypothesis is the *market feedback* hypothesis. That is, first, stock prices communicate information that leads to more efficient investment in innovative projects. Second, this effect comes from stock market learning, where managers glean information from the stock price and take it into account while making R&D investment decisions. The economic rationale is that stock markets aggregate information from a large number of participants who have information from various sources other than from inside firms (Grossman, 1976; Hellwig, 1980; Allen, 1995). There is evidence that managers adjust firm investment policy in response to stock market feedback (Chen, Goldstein, and Jiang, 2007). Moreover, empirical proxies for stock price informativeness, such as firm-specific return variation, is shown to be positively related to capital budgeting quality and firm performance in terms of ROA and sales growth (Durnev, Morck and Yeung, 2004).

Information may come from various sources. For example, other than market feedback from the firm's stock, managers can also obtain information from internal sources or their competitors (Foucault and Fresard, 2013). Therefore, stock market feedback may play a less important role when managers receive more information from alternative sources. Under this hypothesis, we expect exogenous price inefficiency to have a weaker effect on innovative efficiency when managers have more insider information or more information from the stock prices of their competitors. Consistent with this hypothesis, we find that mispricing induced by mutual fund flow-driven pressure has a stronger effect on innovative efficiency when there is less insider information proxied by earnings announcement surprise to the market, as well as lower stock price informativeness proxied by the probability of informed trading (*PIN*) of peer firms (Duart and Young, 2009).

A likely alternative explanation, however, is that stock mispricing affect real efficiency by constraining firms from raising capital (Baker, Stein, Wurgler, 2003; Gao and Lou, 2013; Hau and Lai, 2013). Under this hypothesis, stock mispricing would have a stronger impact on R&D efficiency when firms are financially constrained. However, we find that the relation between stock mispricing and innovative efficiency is concentrated among financially unconstrained firms. This result rules out financing as a potential mechanism that explains the effect of price efficiency on innovative efficiency.

Stock price may also enhance real efficiency by aligning managers' interest with shareholders' interest through incentive contracts (Holmström and Tirole, 1993). As incentive contracts tie managers' compensation to the stock prices, stock prices play an monitoring role by reflecting managers' performance. As a result, a more efficient stock price enhance the effectiveness of incentive contract and thus improve real performance. Using CEO's wealth-performance sensitivity developed by Edmans, Gabaix and Landier (2009) as the measure of managerial incentive, we show that mispricing has a similar effect on innovative efficiency across firms with different level of managerial incentive, suggesting that managerial incentive cannot fully explain the real effect of price efficiency.

The last possible explanation, raised in the behavioral finance literature, is that managers irrationally follow the stock price. One type of the irrational behavior is market timing, that firms seek to raise capital when stock is overvalued (Baker, Stein, Wurgler, 2003). This explanation, however, is unlikely to stand since we find that only firms with deep pocket are affected by stock mispricing. Another type of behavioral bias is that managers follow the stock price to cater to current market sentiment (Polk and Sapienza, 2009). When the stock price is driven by short term investors, stock price may cause managerial myopia as manager forgos long term investment opportunities to boost short term performance (Stein, 1988). Under this hypothesis, stock price should have a stronger effect on innovative efficiency with more holding by short term investors and less holding by long term investors. However, our findings are inconsistent with this hypothesis: First, we find that stock mispricng significantly affects innovative efficiency only with the presence of blockholders (Edmans, 2009), who are the type of investors that are more focused on the long term; Second, the relation between stock mispricng and innovative efficiency increases with the ownership of long term investors but not short term investors based on the classification by Bushee (1998). Overall, our empirical evidences support the market feedback hypothesis over other possible explanations.

This paper contributes to several strands of literature. First, it adds to the literature on the real effects of financial markets.[2] Several previous studies discuss the link between price efficiency and real efficiency. For example, Dow and Gorton (1997) provide a theoretical framework for this relation when managers learn from stock prices. Durnev, Morck, and Yeung (2004) examine the relation between price efficiency and capital budgeting efficiency by using firm specific return variation as a measure of price informativeness. There are also studies that document evidence for market feedback mechanism in investment decisions (e.g., Chen, Goldstein, and Jiang, 2007; Foucault and Gehrig, 2008; Bakke and Whited, 2010). These papers address the endogeneity of stock prices either by structural estimation or cross-sectional variation that is consistent with theoretical predictions. Our paper, however, provides evidence on the causal relation between price efficiency and real efficiency with an exogenous shock to stock prices.

[2]For example, see Luo, 2005; Chen, Goldstein, and Jiang, 2007; Foucault and Gehrig, 2008; Kau, Linck, and Rubin, 2008; Fang, Noe, and Tice, 2009; Bakke and Whited, 2010; Edmans, Goldstein, and Jiang, 2012; Foucault and Fresard, 2012; Foucault and Fresard, 2013; and Ozoguz and Rebello, 2013. See Bond, Edmans, and Goldstein (2012) for a survey.

Second, our paper contributes to the literature on the financing of innovations.[3] In particular, we contribute to the debate as to whether the equity market encourages or impedes longer-term investment. On one hand, the stock market may induce managerial myopia due to takeover threats (Stein, 1988; Shleifer and Summers, 1988) or frequent trading by investors (Bushee, 1998). On the other hand, the equity market involves a large number of investors and sources of information, increasing the chance of recognizing the value of R&D investments compared with relationship-based financing (Rajan and Zingales, 2003; Atanassov, Nanda, and Seru, 2007). Our finding that informative stock prices improve R&D efficiency suggests that given a certain level of efficiency, the stock market is able to recognize the value of R&D investments. This differs from recent studies that show that the stock market fails to value achieved innovations (Cohen, Deither, and Malloy, 2012; Hirshleifer, Hsu, and Li, 2012), as our study shows that the stock market conveys information about the value of future R&D opportunities.

Finally, our study sheds more light on the consequences of stock mispricing. We show that stock mispricing due to mutual fund fire-sales/purchases adversely affects firms' future innovative efficiency by hindering stock market learning by managers. Hence, liquidity shocks can undermine the informational role of the stock market. Our findings imply that stock market frictions can affect the real economy and they add to the literature on the causes and consequences of stock mispricing.[4]

The rest of the paper proceeds as follows. Section 1.2 describes our data and the construction of variables in the empirical analysis. Sections 1.3 and 1.4 discuss the main empirical results and the potential mechanisms. Finally, we provide concluding

[3] For example, see Rajan and Zingales, 2003; Atanassov, Nanda, and Seru, 2007; Brown, Fazzari, and Petersen, 2009; Chava, Oettl, Subramanian, and Subramanian, 2012; Chava, Nanda, and Xiao, 2013.

[4] For example, Dong, Hirshleifer, Richardson, and Teoh (2006), Coval and Stafford (2007), Polk and Sapienza (2009), Dong, Hirshleifer, and Teoh (2012), Edmans, Goldstein, and Jiang (2012), Hau and Lai, (2013), etc.

remarks in Section 1.5.

1.2 Data

We draw our data from five main sources. We obtain stock price information from CRSP, accounting information from Compustat, institutional ownership data from Thompson Reuters 13F data, earnings announcement dates from I/B/E/S, and patent and citation data from the Harvard patent database.[5] The Harvard patent database provides information on patents granted from 1975 to 2010, along with all citations these patents receive over the same period.[6] Using the assignee-PERMNO link provided by the Noah Stoffman, we match the patent applications to public firms in Compustat and CRSP.[7] This allows us to match firms' patenting activities to their financial information. We only include patent data up to 2007 to avoid the estimates from being driven truncation bias in patent applications (Dass, Nanda, and Xiao, 2014) and financial crisis. We include publicly traded firms listed on the New York Stock Exchange, American Stock Exchange, and NASDAQ, and exclude firms in the financial (SIC 6000-6999) and utilities (4900-4999) industries. We also require that firms have at least one non-zero value of R&D investment over the sample period. After merging data from various sources, we have an unbalanced panel with 11,381 firms and 86,180 firm-year observations from 1987 to 2007.

1.2.1 Innovation and Innovative Efficiency

We measure innovation output of innovative activities using the number of patent applications in year $t + n$. Similarly, we measure innovation quality as the number of citations for the patents applied for in year $t + n$. In the empirical analysis we

[5] `https://thedata.harvard.edu/dvn/dv/patent`

[6] A detailed description of patent data can be found in Hall, Jaffe, and Trajtenberg (2001) and Lai et al. (2013).

[7] We thank Noah Stoffman for making the assignee-PERMNO link available. It can be downloaded from `https://iu.app.box.com/patents`

use innovation output (or citations) in same year, one year after, or two years after R&D investment because of an expected lag between $R\&D$ investment and innovative output. The number of patent applications is subject to truncation bias towards the end of the sample period because many patents applied near the end of the sample are not yet granted. So is the number of citations as newer patents tend to accumulate few citations than older patents. Hall et al. (2001) provide a detail discussion on the truncation bias of patent data and propose methods to adjust for this bias. However, Dass, Nanda, and Xiao (2014) find that these adjustment methods are insufficient to correct the truncation bias toward the end of the sample and may generate bias in the estimation. We use two approaches to avoid the empirical results from being driven by the truncation bias. First, we drop the observations in the last three years of the Harvard patent data sample (2008-2010) since Dass et al. (2014) find that the truncation problem is the most severe in the last several years. Second, we follow Hall et al. (2001) and adjust the number of patent applications and citations. For the number of patents, we back out the missing portion of patent applications based on the historical distribution of application-grant lag:

$$NumPat_y^{adj} = \frac{NumPat_y^{raw}}{\sum_{i=0}^{2010-y} frac_i}, \tag{1}$$

where y is the application year, $frac_i$ is the fraction of patents that takes i years to process the application. We estimate $frac_i$ from the sample pf patent applications from 1998 to 2003 and use it to adjust the number of patent applications from 2004 onwards since majority of patents are granted within seven years. For the number of citations, we use the adjustment factor provided by Hall et al. (2001) the adjust the number upward for the new patents.

Recent studies show that innovative efficiency is an important factor of the firm value. Hirshleifer, Hsu, and Li (2012) document that firms that have greater innovative efficiency have higher future operating performance and higher stock returns that cannot be explained by well-known risk factors. In addition, they find that proxies for investor inattention and valuation uncertainty can explain the predictability of innovative efficiency to future stock returns. This finding suggests that innovative efficiency is a factor of the future firm value that has not been fully considered by investors.

1.2.2 Mutual Fund Flow-driven Price Pressure

We use mutual fund flow-driven price pressure as an exogenous shock that causes stock mispricing. Coval and Stafford (2007) find that mutual funds that increase (decrease) existing positions because of a large inflow (outflow) create price pressure in their overlapping holdings. Stocks under such pressure seem to experience a temporary change in price that is reversed over time.[8] Our contention is that such price pressure, unrelated to stock's fundamentals, will cause stock mispricing and therefore reduces price efficiency.

We extract the data on domestic equity fund size and return from the CRSP Survivorship Bias Free Mutual Fund Database, and mutual fund stock holding data from Thompson Reuters, and merge the two datasets using MFLINKS. With mutual fund size and return, we calculate fund flow following the mutual fund literature:

$$Flow_{k,t} = \frac{TNA_{kt} - TNA_{kt-1}(1 + R_{kt})}{TNA_{kt-1}}, \tag{2}$$

where TNA_{kt} is total net assets of fund k at the end of quarter t and R_{kt} is the reported return of fund k over the quarter. We follow Coval and Stafford (2007) and focus on funds that are experiencing extreme inflow or outflow. Funds are regarded as experiencing extreme inflow (outflow) if $Flow_{k,t}$ is above the 90^{th} percentile (below the 10^{th} percentile) of the sample during the quarter. As in Coval et al. (2007) and Cai et al. (2013), flow-driven trading is defined as the aggregate trading by mutual

[8]Such price pressure is used in Edmans, Goldstein, and Jiang (2012) to identify the trigger effect of stock prices on takeover activities. Cai, Cremers, and Wei (2013) show that when the stock price is under such price pressure, the board will rely more on accounting-based performance rather than the stock price in setting CEO compensation. Both papers support the notion that mispricing due to mutual fund fire sales/purchases have real effects on firm decisions and values.

funds experiencing extreme fund flow, scaled by the number of shares outstanding at the beginning of the quarter:

$$Flow\text{-}Driven\ Trades_{i,t} \tag{3}$$
$$= \frac{\Sigma_k(max(0,\Delta Holdings_{i,k,t})|Flow_{k,t}>90^{th}pctl.)-(max(0,-\Delta Holdings_{i,k,t})|Flow_{k,t}<10^{th}pctl.)}{SharesOutstanding_{k,t-1}},$$

where $\Delta Holdings_{i,k,t}$ is change in the number of shares held by mutual funds. We consider only the increase (decrease) in holdings by funds experiencing inflow (outflow), as those trades are more likely to be flow-driven. We then subtract the sells by funds with outflow from the purchases by funds with inflow to get the net flow-driven trades for a stock. We require a stock to be owned by at least 5 funds in calculating net fund flow-driven trades.

We follow Cai et al. (2013) and assign a variable to each firm-quarter that equals to 1 if the net fund flow-driven trade in Equation (3) is positive, -1 if the net fund flow-driven trade is negative, and 0 otherwise. We then take an average of this variable for all four quarters of a fiscal year and use the absolute value of this average as the instrumental variable. We also conduct our analysis using positive and negative stock price pressure as separate instrumental variables.

Both Coval et al. (2007) and Cai et al. (2013) show that there is a positive (negative) abnormal return for stocks under positive (negative) fund flow-driven price pressure, with the stock price reversing eventually in both cases. We find a similar pattern of stock returns after price pressure in our data. Figure 1 and 2 show the cumulative abnormal return (CAR) over equal-weight market return around the mutual fund fire sales and purchases identified each quarter.[9] Figure 1 shows that stock price goes as far as 3% below market after mutual fund negative pressure and reverse to close to zero in two years. Similar but opposition observation is found for mutual fund's positive pressure as shown in Figure 2, though it takes shorter time to reverse.

[9]The curve is smoothen by taking a three-month moving average.

Both of these figures shows that stock price movement after mutual fund flow-driven pressure are reversed over time, consistent with previous studies on mutual fund fire sales (Coval et al., 2007; and Cai et al., 2013) and reflect stock mispricing under such pressure.

Table 1 presents summary statistics of the variables used in the empirical analyses. The mean value of innovation output measured by *Ln(Patent)* is 0.511 with standard deviation of 1.052. The mean value of *Ln(R&D)* is 1.014 and standard deviation is 1.524. As previously mentioned, *Pressure* is a variable ranging from 0 to +1, with an increment of 0.25 indicating a significant mutual fund pressure in one out of four quarters. This variable has mean value of 0.035 and standard deviation of 0.103. Other firm and industry variables indicated in the table serve primarily as controls in our regression analysis.

1.3 Empirical Design and Results

1.3.1 Price Inefficiency and Innovative Efficiency

We test the effect of stock inefficiency on innovative efficiency using the following model:

$$\begin{aligned} Ln(Innovation)_{t+n} = {} & \alpha_1 + \beta_1 Ln(R\&D)_{t+1} + \beta_2 Ln(R\&D)_{t+1} \times Pressure_t \\ & + \beta_3 Pressure_t + \gamma_1' CONTROL + \phi_i + \psi_t + \epsilon_{i,t}. \end{aligned} \tag{4}$$

Here ϕ_i and ψ_{t+1} stand for fixed effects for firm i and year $t + 1$, respectively. *Ln(Innovation)* is either measured by the adjusted number of patent applications or the adjusted number of total citations on the patents. *Ln(R&D)* measures the natural logarithm of R&D expenditure in million dollars. We do not scale R&D by sales or assets because the dependent variable is also unscaled and correlated with firm size. To capture the correlation with firm size, we instead include *Ln(Assets)* in the regression. *CONTROL* includes a number of firm and industry characteristics that are likely to affect firms' R&D investment and innovation. In addition to firm size, we include firm characteristics such as *Leverage*, *CAPEX*, *Tangibility*, *ROA*, *Q*, and *SA Index*. In addition, we also follow Aghion, Bloom, Blundell, Griffith, and Howitt (2005) and control for product market competition by including the *Herfindahl Index* at 4-digit SIC industry level, along with $Herfindahl^2$ to capture any non-linear effect of competition on innovation.

The above model tests how stock mispricing in year t affect the efficiency of R&D investment in year $t+1$. The estimate of β_1 reflects the efficiency of R&D investment when stock prices are not affected by mutual fund flow-driven pressure. $\beta_1 + \beta_2$ measures the efficiency of R&D following stock mispricing caused by mutual fund pressure. If price efficiency has a positive causal effect on innovative efficiency but this role is hindered by exogenous mispricing due to mutual fund pressure, then one would expect β_2 to be significantly negative while β_1 is significantly positive.[10] Chen, Goldstein, and Jiang (2006) show that firms' investments including R&D are more sensitive to their stock prices when the stock prices are more informative, suggesting that managers learn from stock prices for making R&D investment decisions and that depends on the information quality of the stock prices. Here we directly test the implication of stock price informativeness to the efficiency of R&D investment, as when stocks are mispriced, informativeness of stock prices clearly declines.

The results are presented in Table 2. The estimate of β_1 is significant at the 1% level across all specifications, indicating that the same amount of R&D on average leads to more innovation output. Our variable of interest, β_2, is significantly positive at 5% for the number of patents in year $t+2$ and $t+3$ and is significant at 1% for the total number of citations of patents applied in all the subsequent three years. This result is consistent with our prediction that price inefficiency reduces innovativ efficiency. The economic magnitude for the effect of mispricing is substantial. For

[10]To avoid the estimates from being driven by the multicollinearity between $Ln(R\&D)_{t+1} \times Pressure_t$ and $Pressure_t$, we use the demeaned value of *Ln(R&D)* when computing the interaction term.

example, based on estimates in column (2) the estimated β_1 is 0.215 while β_2 is -0.04, suggesting that the efficiency of of R&D investment in terms of generating patents reduces by 4.7% when there is stock mispricing caused by mutual fund pressure in one quarter. The estimated effect on the number of citations is larger in magnitude. Based on the estimates in column (5), the efficiency of R&D in terms of generating citations reduces by 26.2%. The larger impact on citations suggest that mispricing not only reduces R&D efficiency in terms of quantity of innovation, but also reduces R&D *effectiveness* in terms of the quality of innovation.

Another interesting observation is that the estimated coefficient for *Pressure* is not significant. This estimate suggests that stock mispricing has no direct effect on innovation output, but it affects innovation by influencing the efficiency R&D investment. One plausible explanation is that price inefficiency leads to suboptimal R&D decisions. More detailed discussion regarding the mechanism is in the later session. The estimated coefficients on other control variables are mostly consistent with the literature: the level of innovation is higher for firms with larger size, lower leverage, higher tangibility, and higher Tobin's Q. The estimated coefficient for the linear term of *Herfindahl* is positive and that for the quadratic term is negative. These estimates, though insignificant, also suggest an inverted U-shaped relationship between product market competition and innovation.

One endogeneity concern with respect to this result is that mutual funds' trading under fund flow pressure may not be completely liquidity-driven, but still based on information about expected firm performance. In this scenario, mutual funds trading is endogenous and may have predictability for firms' innovative efficiency. If this is the case, one would expect mutual funds' purchases to predict higher innovative efficiency and vice versa for mutual fund sales. To test this possibility, we separate the price pressure into two components: one caused by mutual fund purchases (*Positive Pressure*) and the other caused by mutual fund sales (*Negative Pressure*). For each firm-quarter, *Positive Pressure* (*Negative Pressure*) indicator equals 1 if *Flow-Driven Trades* computed in Equation (3) is positive (negative), and 0 otherwise. We then use the average value of the indicators over the four quarters to measure the price pressure in two directions for each firm-year. Figure 1 and 2 show the stock price movement after mutual fund fire purchases and sales based on the above measures. The price drift in the direction of mutual fund trades and the reversal indicate that these trades in both direction cause mispricing in the stock. To test the differential effect of positive pressure and negative pressure on innovative efficiency, we interact *Ln(R&D)* with the two pressure variable separately in the regression similar to Equation (4). If mutual fund pressure predicts performance, positive pressure should be related to higher innovative efficiency. But if mutual fund pressure causes change in performance, then mutual fund pressure in both direction causes price inefficiency and therefore should reduce innovative efficiency.

We present the results in Table 3. In column 1 to 3, we show estimates of regressions with patent as the dependent variable. The estimation shows that only positive pressure significantly reduces the efficiency of R&D investment. In column 4 to 6, where we show the results for citations, both positive pressure and negative pressure have significantly negative effect on the efficiency of R&D. The effect of the two pressures are also similar in terms of magnitude. For example, based on estimates in column 5, positive (negative) mutual fund price pressure reduces R&D efficiency by 16.2% (20.6%). The result that mutual fund price pressure in either direction has the same effect on R&D efficiency is an evidence against the endogeneity of mutual fund pressure and supports our causal interpretation of the findings.

1.4 Mechanism for the Real Effect of Price Efficiency

The previous section shows that stock price informativeness has a causal effect on innovative efficiency. In this section we study various possible mechanism that may explain the real effect of price efficiency.

1.4.1 Market Feedback

The first possible explaination is that managers improve R&D efficiency by gleaning information from the stock prices. Studies have shown that stock prices contain valuable information that managers do not have and that these prices can potentially guide managers in making corporate investment decisions. The economic rationale is that stock markets aggregate information from a large number of participants who have information from various sources other than from inside firms (Grossman, 1976; Hellwig, 1980; Allen, 1995). There is evidence that managers adjust firm investment policy in response to stock market feedback (Chen, Goldstein, and Jiang, 2007). Moreover, empirical proxies for stock price informativeness, such as firm-specific return variation, is shown to be positively related to capital budgeting quality and firm performance in terms of ROA and sales growth (Durnev, Morck and Yeung, 2004).

Allen (1993) argues that the informational role of the stock market is more important when the production process is complex and there is no consensus on what is the optimal action for the manager. In the case of innovative activities, any new insight provided by the stock market may be particularly important if there is no other reliable source of information for managers to learn about the prospect of the firm's technology. Moreover, even if the stock market is not able to provide feedback regarding the technology of innovation, the market may still have some useful information about the prospect of innovative projects in terms of, say, market demand and competition. Therefore, it is plausible that the stock market can provide useful feedback and guide managers in making R&D investment decisions. In fact, the U.S. stock market has been attracting foreign high-technology companies to cross-list their stocks, possibly due to its ability to value high-tech companies (Pagano, Roell, and

Zechner, 2002). This suggests that the U.S. stock market may provide useful feedback about technological investment for managers. Therefore, it is possible that the stock market aggregates and reflects private information about the prospect of innovative activities and, managers are able to make use of this information and improve innovative efficiency.

Information may come from various sources. For example, other than market feedback from the firm's stock, managers can also obtain information from internal sources or their competitors (Foucault and Fresard, 2013). Therefore, stock market feedback may play a less important role when managers receive more information from alternative sources. Under this hypothesis, we expect exogenous price inefficiency to have a weaker effect on innovative efficiency when managers have more insider information or more useful information from the stock prices of their competitors.

We first test how managers' insider information influence the relation between price efficiency and innovative efficiency. As an empirical proxy for managers' insider information, we use market surprise to firms' earnings announcement. If manager has private information about the earnings of the firm, the information release of firms' earnings should generate larger stock price movement (Chen, Goldstein, and Jiang, 2006). We measure earnings surprise by computing the absolute value of the cumulative abnormal return over equal-weight market return from two days before to two days after earnings announcement. And we reestimate Model (4) in three subsamples sorted by earnings surprise. The prediction is that if managers rely less on stock market feedback, price inefficiency should have less effect on innovative efficiency when insider information (earnings surprise) is higher.

We present the results in Table 4. For brevity we only show results for innovation in $t+2$ hereafter but we find consistent results with innovation in $t+1$ and $t+3$. In column 1 to 3, the coefficient for $Ln(R\&D)_{t+1} \times Pressure$ is negative but only significant in the middle tertile. In the regression using citations as the dependent variable, the estimate for the interaction term is significant at 1% in all subsamples. Moreover, the economic magnitude is monotonically decreasing from the bottom tertile to the top tertile. Based on the estimates in column 4 to 6, mutual fund pressure reduces innovative efficiency by 18% in the subample with earnings surprise in the top tertile, while the same pressure reduces innovative efficiency by 27.7% in the bottom tertile. This result is consistent with our prediction, that stock mispricing has a greater effect on innovative efficiency when managers have less insider information.

Another source of information is industry peers (Foucault and Fresard, 2013; Ozoguz and Rebello, 2013). Foucault and Fresard (2013) discuss the market feedback channel from the stock price of industry peers. Given a firm competes with industry peers in the same product market, the stock price of the peers should also convey information relevant to the firm. For the purpose of market learning, the firm's own stock price and peer's stock price are alternative sources of information that can be substitutable to some extent. Consistent with this prediction, they find that a firm's investment is more (less) sensitive to the stock price of their industry peers (their own) when the stock prices of industry peers are more informative. If price efficiency enhances real efficiency by providing market feedback, such effect may be weaker if the firm receive useful information from the peers' stock prices. We therefore test how the effect of stock mispricing on innovative efficiency is related to the informativeness of peer's stock prices.

We first focus on firms that share the same three-digit SIC classification. For proxy of price informativeness we use the probability of informed trading (*PIN*) measure. This measure developed by Easley, Hvidkjær, and O'Hara (2002) captures the amount of private information in the stock. Duarte and Young (2009) revise the measure to further separate the information asymmetry component from the liquidity component. We use the *PIN* measure constructed by Duarte and Young to measure the informativeness of the peers' stock prices.[11] We take the average value of *PIN* for all the peers in the same three-digit SIC industry and again estimate Model (4) in tertiles sorted by peers' average *PIN*. The prediction is that the coefficient estimate for $Ln(R\&D)_{t+1} \times Pressure$ is significantly negative and greater in magnitude in the subsample with lower peers' average *PIN*.

We show the results in Panel A of Table 5. Consistent with our prediction, we find that the interaction term $Ln(R\&D)_{t+1} \times Pressure$ for innovation is only significant in the bottom tertile in terms of average peers' *PIN*. This result suggests that stock mispricing does not have a significant adverse effect on innovative efficiency if there is a lot of private information in the peers' stock prices. This is consistent with the market feedback hypothesis since peers' stock price can act as an substitute to the firm's own stock price as a source of market feedback based on the study by Foucault and Fresard (2013).

Hoberg and Phillips (2011) develop a new industry classification called Text-based Network Industry Classification (TNIC). They use textual analysis on the product description in firms' 10-K filings to identify firms with similar products. For each firm, they find peer firms that produce similar products based on this method. The threshold of product closeness is decided in order to match the SIC code in terms of unconditional likelihood of two random firms being in the same industry. For example, under the classification of TNIC3, the unconditional likelihood that two random firms are in the same TNIC3 industry is 2.05%, which matches the unconditional likelihood of two random firms being in the same three-digit SIC industry (Hoberg and Phillips, 2011).[12] Since learning from peers' stock prices is more relevant among firms producing similar products, we adopt the TNIC3 classification as an alternative

[11] We thank Jefferson Duarte and Lance Young for making their data available. The data can be downloaded from `http://www.owlnet.rice.edu/~jd10/publications.htm`

[12] We thank Gerard Hoberg and Gordon Phillips for making the TNIC data available. The data can be downloaded from `http://alex2.umd.edu/industrydata/industryclass.htm`

to three-digit SIC to test the market feedback hypothesis.

As previously discussed, we test the relation between the effect of stock mispricing on innovative efficiency with average peers' stock price informativeness. But this time we find the peer firms based on the TNIC3 classification. We again sort the sample to tertiles based on the average *PIN* of TNIC3 peers. The results are presented in the Panel B of Table 5. For regression using citations as the innovation output (column 4 to 6), it shows that $Ln(R\&D)_{t+1} \times Pressure$ is significantly negative only in the middle and bottom tertiles of average peers' *PIN*. This is again consistent with our prediction as stock mispricing has no significant effect on innovative efficiency when the amount of private information in peers' stock price is high. For regressions using patent as the dependent variable, we find no significant effect in any subsample, though the coefficient magnitude is also monotonically decreasing with peers' *PIN*. The results with two different industry classifications support the argument that loss of market feedback due to mispricing contribute to lower innovative efficiency, and this effect is weaker when firms have more information from peers' stock prices.

The informational role of peers' stock prices depend not only on the amount of information in the stock price, but also how relevant peers' stock price is to the firm. Presumably, information from peers' stock price would be more useful to the firm if firm value is more correlated with the peers. Foucault and Fresard (2013) find that firm's investment is more sensitive to peers' stock prices when the firm has higher fundamental correlation with its peers. Here we also test whether the effect of stock mispricing on innovative efficiency is related to the fundamental correlation between the firm and its peers. We compute the correlation of stock return betwene the firm and its peers. To not differentiate between positive or negative correlation, we use the absolute value of the correlation as the measure of fundamental relatedness. Similar to previous tests, we sort the sample into tertiles based on this fundamental relatedness measure. We again define peer firms both using three-digit SIC classification and

TNIC3 classification.

The results are reported in Table 6. Similar to previous tests, when using patents as the innovation measure, most of the subsamples do not have significant loading on $Ln(R\&D)_{t+1} \times Pressure$, though it is still noted that all the estimates are negative and the magnitude is larger for the subsamples with medium or low return correlation. For regressions using citations as the innovation measure, the coefficient estimate on the interaction term is significant in all the subsamples. But for both results with SIC and TNIC classification, the effect of mispricing is lower for subsample with the highest return correlation with peers. For example, column 4 to 6 of Panel B show that the coefficient for $Ln(R\&D)_{t+1} \times Pressure$ in the high-return-correlation sample is -0.267, while that for the medium- and low-return-correlation sample is -0.447 and -0.419, respectively. So the effect of stock mispricing in the higher-return-correlation sample is about 40% smaller in magnitude than the rest of the sample. This result is consistent with our prediction as well as Foucault and Fresard's (2013) finding that stock price information is less important when the firm is fundamentally more related with its industry peers.

Overall, our empirical evidences support the market feedback hypothesis, that price efficiency improve innovative efficiency by providing informative signals. This informational role, however, is weaker when firms have more insider information, have more information from peers' stock prices, and fundamentally more correlated with industry peers. Next we explore other alternative explanations.

1.4.2 Financing Effect

One alternative channel through which price efficiency affects innovative efficiency is financing. When stock is mispriced, it may constraint firms' access to equity capital and thus reduces the efficiency of R&D investment. On the other hand, if stock price is efficient, firms may raise equity capital more easily and be able to enhance innovative efficiency. In fact, a number of studies in the extant literature show that the equity market has a supply effect firms' investment (See Baker (2009) for a survey). For example, Baker, Stein, and Wurgler (2003) show that investment-Q sensitivity is greater among equity-dependent firms. Their explanation is that stock prices can, in themselves, influence investment by easing or worsening a firm's financial constraints. Hau and Lai (2009) examine mutual funds' fire sales during the financial crisis and show that it caused a decrease in the investment of non-financial firms. And they find that this effect is concentrated among the financially constraint firms. Gao and Lou (2013) also use mutual fund fire sales but look directly at firms financing activities. They find that firms dependent on external financing issue both more equity and debt when the stock is over-priced. All of these studies show that the equity market has a real effect on firms' investment by affecting financing.

If firms are not able to invest at the optimal level due to financial constraint, one would predict financial constraint to have a negative effect on innovative efficiency. However, as Jensen (1986) argues, agency problem can arise with free cash flow. Financial constraint may play a disciplining role on managers by reducing free cash flow. In fact, Almeida, Hsu, and Li (2013) find that financially constrained firms have higher innovative efficiency. Therefore the direct relation between financial constraint and real efficiency is yet conclusive. However, for the equity market to have a real effect on firm's efficiency through financing, financial constraint has to be binding.

To test this hypothesis, we follow previous approach and sort the sample into tertiles based on proxies of financial constraint. The first proxy we use is *SA Index* proposed by Hadlock and Pierce (2010). It is computed as a function of firms' size in terms of total assets and firm age. Detailed description of the variable is available in the Appendix. We test Model (4) in the three subsamples sorted by *SA Index* and present the results in Panel A of Table 7. For regressions with patent as the innovation measure, stock mispricing reduces the efficiency of R&D only for the firms in the bottom tertile of financial constraint. When testing the R&D-citation relation, stock mispricing due to mutual fund flow-driven pressure have a significantly negative effect on the relation only for firms with medium and low level of financial constraint.

The next empirical proxy for financial constraint is the *WW Index* by Whited and Wu (2006). This index takes into account firm's cash flow, dividend policy, long term debt, total assets, industry growth and firm's sales growth. We again leave the detailed description for the variable to the Appendix. Panel B of Table 7 shows estimates of Model (4) in subsamples sorted by *WW Index*. The results are again similar to the previous one, that stock mispricing reduces patent-based efficiency only in the subsample with low financial constraint, and citation-based efficiency in the subsamples with medium and low level of financial constraint. Moreover, the effect of mispricing is monotonically decreasing with financial constraint. In other word, price efficiency has a stronger effect on innovative efficiency as firms have more financial slack.

The above results are not consistent with the financing effect hypothesis, as stock mispricing affect innovative efficiency exactly when financial constraint is not binding. However, this finding can be consistent with the market feedback explanation. Since firms need the financial slack to be able to adjust their investment when they receive informative signals from stock prices, it is likely that firms benefit more from market feedback when they are financially unconstrained (Chen, Goldstein, and Jiang, 2006). Therefore, the evidences thus far are supportive of the market feedback hypothesis but not the financing effect hypothesis.

1.4.3 Managerial Incentive

Price efficiency may enhance real efficiency by incentivizing the manager. From the literature on optimal incentive contracts (e.g., Holmström, 1979), we would expect managers to be offered stronger incentive contracts when the firm's stock price is informative and provides a more precise reflection of firm value.[13] As manager's compensation is tied to firm value, managers will have a stronger incentive to take value-maximizing actions for the firms. On the other hand, it has been argued in the literature that the stock markets coupled with strong incentives can distort the investment process and induce managerial myopia (Stein, 1988). Managers, in an attempt to boost short term price rises may forgo long term investments to boost short term performance and, as a result, compromise investment in innovative activities.

Since a more informative stock price also facilitates stock market learning, we might expect incentives and stock market learning to be complementary mechanisms through which the stock market affects real efficiency, including R&D investment. As Bond et al. (2012) have discussed, both effects relate to the informational role of stock prices. Incentivized managers may also pay more attention to the stock prices and, as a consequence, extract more information from stock prices.

We study the role of incentive contracts in the real effect of price efficiency on innovative efficiency. Specifically, we use CEO's *scaled wealth-performance sensitivity* developed by Edmans, Gabaix and Landier (2009) as the empirical proxy for the strength of managerial incentives. It measures the change in the wealth of the CEO when there is a one-hundred-percentage change in firm value, scaled by annual pay.[14] Similar to Section 1.4.1 and 1.4.2, we sort the sample into tertiles based on *scaled wealth-performance sensitivity*. The estimates are reported in Table 8. Due to limited data availability on CEO compensation, the sample size here is substantially smaller than that in the previous sections. Nevertheless, we still find a significantly negative effect of stock mispricing on innovative efficiency in all the subsamples when focusing on citations as the innovation measure. However, there is no significant trend in

[13]Holmström and Tirole (1993) develop a model to argue that not only are strong incentive contracts optimal when stock prices are more efficient, but also that strong incentive contracts can induce managers to enhance stock price efficiency.

[14]The data is available at `http://finance.wharton.upenn.edu/~aedmans/data.html`

the effect of stock mispricing across tertiles. For example, in columns 4 to 6, the coefficient on the interaction between *Ln(R&D)* and *Pressure* is -0.297 for firms in the top tertile while that is -0.286 for firms in the bottom tertile. The insignificant difference in the effect of price mispricing across subsamples suggest that incentive mechanism cannot fully explain the effect of price efficiency on innovative efficiency.

1.4.4 Market Short Termism

Another possible mechanism through which stock price affects real efficiency is that managers irrationally follow the stock price. There are two explanations for this behavior. One reason for the irrational behavior is market timing, that firms are able to raise capital when stock is overvalued (Baker, Stein, and Wurgler, 2003; Gao and Lou, 2013). This explanation, however, has been ruled out since we find stock mispricing affect innovative efficiency only when firms are not constrained financially.

Another explanation for the behavioral bias is that managers follow the stock price to cater to current sentiment (Polk and Sapienza, 2009). When the stock price is driven by short term investor, stock price may cause managerial myopia as manager forgo long term investment opportunities to boost short term stock price (Stein, 1988). Managers may take on negative NPV projects when the stock is over-priced and forgo positive NPV projects when the stock is under-priced.

As suggested by Stein (1996) and Polk and Sapienza (2009), the catering behavior is more likely to take place when the shareholder horizon is short. Under this hypothesis, stock price should have a stronger effect on innovative efficiency with larger holding by short term investor and less holder by long term investors. To test this, we look into the type of shareholders holding the stocks. First, we check whether firms have blockholders. Blockholders are deemed to be long term investors and play a more active role in governance. Edmans (2009), for example, shows that blockholders can mitigate managerial myopia. The rationale is that blockholders, who are less subject to short-sale constraints compared to other shareholders, have greater incentive to acquire information and monitor managers by trading on information. As a result, blockholders will incorporate more information about the fundamental value of the firms into stock prices and will be less sensitive to short-term performance.

We compare between firms with or without blockholders in terms of the effect of stock mispricing on innovative efficiency. To do this we estimate Model (4) in the two subsamples based on presence of blockholders. Results reported in Table 9 show that the interaction between *Ln(R&D)* and *Pressure* is significant only among firms with blockholders. This is inconsistent with catering mechanism as blockholders tend to have longer horizon.

Next, we follow Bushee's (1998) classification of institutional investors: dedicated investors who have concentrated portfolios and low portfolio turnover; quasi-indexers who have diversified portfolios and low turnover; and transient investors who have diversified portfolios and high turnover. Among the three categories, transient investors have short-term horizon while dedicated investors and quasi-indexers have longer horizon. If stock mispricing affect innovative efficiency due to managers' catering behavior, then the effect is expect to be increasing with the ownership of transient investors. We define transient investors as short term investors and group dedicated investors and quasi-indexers as long term investors and examine how their ownership interacts with the effect of stock mispricing on innovative efficiency.

For this test, we need to include the ownership by both type of investors since they are highly correlated across firms.[15] We add triple interactions among *Ln(R&D)*, *Pressure*, and long-term or short-term investor ownership. We also control for the pair-wise interactions among all these variables in the regression. If catering behavior is what explains the relation between mispricing and innovative efficiency, then

[15] The correlation between long term investor and short term investors is 0.52 in our sample.

Ln(R&D)$_{t+1}$ × *Pressure* × *Short-Term Investor Ownership* should be significantly negative.

We show the estimates in Table 10. While *Ln(R&D)*$_{t+1}$ × *Pressure* × *Long-Term Investor Ownership* is significantly negative, *Ln(R&D)*$_{t+1}$ × *Pressure* × *Short-Term Investor Ownership* is not. This suggests that the effect of mispricing on innovative efficiency is increasing with the ownership of long-term investors but not short-term investors. This is again not consistent with the market short termism hypothesis since the presence of short term investors does not cause larger negative effect of mispricing.

However, we believe that the above finding is again consistent with market feedback hypothesis. Blockholders and long-term investors can promote stock market learning by acting as patient shareholders that are less sensitive to short term performance. When managers receive positive signal from the stock price, they can act upon by increasing the investment without worrying about past underperformance. Aghion, Van Reenen, and Zingales (2013) find that higher institutional ownership is related to more corporate innovation and they argue that institutional investors encourage more innovation by mitigating managers' short term career risk. Therefore, it is likely that long-term investors increase the real effect of stock prices by facilitating market learning.

1.5 Conclusion

This paper examines whether price efficiency improve innovative efficiency. We find that stock price inefficiency caused by exogenous mutual fund fire sales or purchases reduces efficiency of future R&D investment. This relation is robust after controlling for a number of firm and industry characteristics. The relation is stronger when market feedback is deemed to be more important. Specifically, stock mispricing has greater effect on innovative efficiency when managers have less insider information, receive less information from peers' stock prices, or when the firm is fundamentally less correlated with peer firms. Therefore, our findings suggests that stock markets improve real efficiency by serving as a means of aggregating investors' information and providing managers with "feedback" that guides their investment decisions.

Several alternative explanations are examined and seem unlikely to explain the above relation. First, the endogeneity of mutual fund trading is not likely to explain our findings since both positive and negative price pressure caused by mutual fund flow lead to lower innovative efficiency. Second, the effect of stock mispricing on innovative efficiency does not come through financing since the relation between stock mispricing and innovative efficiency is concentrated among financially unconstrained firms. Third, managerial incentive cannot fully explain the results since the relation between stock mispricing and innovative efficiency does not vary significantly based on managers' wealth-performance sensitivity. Finally, the real effect of price inefficiency is unlikely to be driven by market short termism since the effect increases with the ownership of long term investors but not short term investors.

Our evidence is supportive of the idea that stock markets recognize the value of future R&D investment opportunities and provide valuable feedback to managers. This finding contributes to the debate as to whether stock markets facilitate or hinder innovative activities or other types of long-term investment. This study has potential policy implications as regulations that aim to improve the information environment of the financial market may have a significant impact on the efficiency of innovative activities. Hence, financial markets have an economic role to play beyond that of simply providing financing. Our paper also suggests that an under-appreciated cost of stock market disruptions may be the poorer investment decisions by firms when there is an interruption in the market-feedback channel.

Table 1: Summary Statistics For Chapter 1.

This table presents summary statistics of the main variables used in our analyses. We winsorize all the variables at the 1st and 99th percentiles. All the variables are defined in the Appendix.

	N	Mean	Median	Std. Dev.
Ln(Patent)	86,180	0.511	0.000	1.052
Ln(Citation)	86,180	1.029	0.000	1.983
Ln(R&D)	86,180	1.014	0.000	1.524
Pressure	86,180	0.035	0.000	0.103
Positive Pressure	86,180	0.020	0.000	0.079
Negative Pressure	86,180	0.019	0.000	0.078
Ln(Assets)	86,180	4.734	4.600	2.068
Leverage	86,180	0.227	0.186	0.217
CAPEX	86,180	0.088	0.049	0.126
Tangibility	86,180	0.273	0.209	0.222
ROA	86,180	-0.076	0.028	0.380
Q	86,180	2.133	1.475	1.932
SA Index	86,180	1.402	1.404	1.971
Herfindahl	86,180	0.220	0.171	0.169
Absolute Earnings Announcement CAR	63,457	0.073	0.060	0.055
PIN of Peer Firms (SIC3)	74,515	0.185	0.181	0.045
PIN of Peer Firms (TNIC3)	34,686	0.158	0.154	0.047
Absolute Stock Corr. with Peer Firms (SIC3)	70,098	0.365	0.358	0.218
Absolute Stock Corr. with Peer Firms (TNIC3)	39,812	0.375	0.370	0.221
WW Index	80,541	-0.225	-0.223	0.128
Wealth-Performance Sensitivity	19,892	41.645	7.598	132.239
Blockholder	86,180	0.592	1.000	0.492
Short-Term Investor Ownership	86,180	0.081	0.042	0.100
Long-Term Investor Ownership	86,180	0.248	0.196	0.218

Table 2: Mutual Fund Flow-driven Price Pressure and Innovative Efficiency.

This table presents estimates from firm fixed effects regressions where the dependent variables are measures of future innovation output and the independent variable of interest is $Ln(R\&D)_{t+1} \times Pressure$. The following control variables are also included in the regressions: *Ln(Assets)*, *Leverage*, *CAPEX*, *Tangibility*, *ROA*, *Q*, *SA Index*, *Herfindahl*, and *Herfindahl²*. Year fixed effects are also included. *t*-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variables:	$Ln(Pat)_{t+1}$ (1)	$Ln(Pat)_{t+2}$ (2)	$Ln(Pat)_{t+3}$ (3)	$Ln(Cite)_{t+1}$ (4)	$Ln(Cite)_{t+2}$ (5)	$Ln(Cite)_{t+3}$ (6)
$Ln(R\&D)_{t+1} \times$ Pressure	0.005	-0.040**	-0.048**	-0.188***	-0.360***	-0.316***
	(0.33)	(-2.37)	(-2.57)	(-6.36)	(-11.01)	(-8.48)
$Ln(R\&D)_{t+1}$	0.157***	0.215***	0.160***	0.231***	0.343***	0.220***
	(16.44)	(19.83)	(15.61)	(14.09)	(18.65)	(12.70)
Pressure	-0.025	-0.016	-0.005	0.005	-0.006	0.042
	(-1.28)	(-0.79)	(-0.23)	(0.10)	(-0.12)	(0.82)
Ln(Assets)	0.165***	0.129***	0.105***	0.120**	0.062	0.047
	(4.78)	(3.72)	(2.81)	(2.08)	(1.07)	(0.74)
Leverage	-0.111***	-0.114***	-0.125***	-0.334***	-0.342***	-0.347***
	(-5.18)	(-5.18)	(-5.29)	(-6.84)	(-6.88)	(-6.71)
CAPEX	-0.057***	-0.017	0.008	-0.062	0.041	0.067
	(-2.93)	(-0.86)	(0.40)	(-1.34)	(0.87)	(1.37)
Tangibility	0.097***	0.099***	0.083***	0.284***	0.297***	0.286***
	(3.10)	(3.25)	(2.63)	(4.27)	(4.39)	(3.98)
ROA	-0.014	-0.004	0.009	-0.048**	-0.052**	-0.003
	(-1.56)	(-0.41)	(1.03)	(-2.07)	(-2.24)	(-0.15)
Q	0.013***	0.013***	0.011***	0.035***	0.033***	0.024***
	(6.76)	(6.37)	(5.53)	(7.29)	(6.64)	(4.80)
SA Index	0.079**	0.079**	0.063*	-0.045	-0.020	-0.009
	(2.29)	(2.30)	(1.69)	(-0.78)	(-0.34)	(-0.14)
Herfindahl	0.076	0.117	0.095	0.257	0.226	0.200
	(0.92)	(1.43)	(1.12)	(1.51)	(1.28)	(1.06)
$Herfindahl^2$	-0.038	-0.082	-0.072	-0.221	-0.218	-0.206
	(-0.40)	(-0.90)	(-0.78)	(-1.20)	(-1.15)	(-1.02)
Constant	-0.543**	-0.431**	-0.239	0.413	0.538	0.724*
	(-2.52)	(-2.02)	(-1.03)	(1.15)	(1.50)	(1.85)
Adjusted R^2	0.836	0.823	0.808	0.728	0.709	0.691
Observations	86,180	82,749	79,245	86,180	82,749	79,245
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Mutual Fund Flow-driven Price Pressure and Innovation Efficiency: Positive Pressure versus Negative Pressure.

This table presents estimates from firm fixed effects regressions where the dependent variables are measures of future innovation output and the independent variable of interest are $Ln(R\&D)_{t+1} \times$ Positive Pressure and $Ln(R\&D)_{t+1} \times$ Negative Pressure. The following control variables are also included in the regressions: *Ln(Assets)*, *Leverage*, *CAPEX*, *Tangibility*, *ROA*, *Q*, *SA Index*, *Herfindahl*, and *Herfindahl*^{2}. Year fixed effects are also included. t-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variables:	$Ln(Pat)_{t+1}$ (1)	$Ln(Pat)_{t+2}$ (2)	$Ln(Pat)_{t+3}$ (3)	$Ln(Cite)_{t+1}$ (4)	$Ln(Cite)_{t+2}$ (5)	$Ln(Cite)_{t+3}$ (6)
$Ln(R\&D)_{t+1} \times$ Positive Pressure	-0.010	-0.048**	-0.077***	-0.150***	-0.267***	-0.306***
	(-0.51)	(-2.19)	(-2.88)	(-3.89)	(-5.90)	(-5.63)
$Ln(R\&D)_{t+1} \times$ Negative Pressure	0.026	-0.027	-0.023	-0.191***	-0.379***	-0.297***
	(1.24)	(-1.23)	(-1.07)	(-5.10)	(-9.42)	(-7.29)
$Ln(R\&D)_{t+1}$	0.156***	0.215***	0.161***	0.232***	0.345***	0.222***
	(16.37)	(19.82)	(15.59)	(14.11)	(18.71)	(12.76)
Positive Pressure	-0.016	0.017	-0.023	0.061	0.136**	0.018
	(-0.70)	(0.68)	(-0.85)	(1.11)	(2.27)	(0.27)
Negative Pressure	-0.023	-0.023	0.006	-0.037	-0.086	0.007
	(-0.97)	(-0.90)	(0.22)	(-0.67)	(-1.44)	(0.12)
Adjusted R^2	0.836	0.823	0.808	0.728	0.709	0.691
Observations	86,180	82,749	79,245	86,180	82,749	79,245
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Insider Information, Mutual Fund Flow-driven Price Pressure and Innovative Efficiency.

In this table, we sort firms into tertiles based on the absolute value of earnings announcement CAR as a measure of insider information and estimate Model (4) in the three subsamples. The dependent variables are measures of future innovation output and the independent variable of interest is $Ln(R\&D)_{t+1} \times Pressure$. The following control variables are also included in the regressions: *Ln(Assets)*, *Leverage*, *CAPEX*, *Tangibility*, *ROA*, *Q*, *SA Index*, *Herfindahl*, and *Herfindahl*^{2}. Year fixed effects are also included. t-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variables:	Ln(Patent)_{t+2}			$\text{Ln(Citation)}_{t+2}$		
Subsample:	High (1)	Medium (2)	Low (3)	High (4)	Medium (5)	Low (6)
$\text{Ln(R\&D)}_{t+1} \times$ Pressure	-0.021 (-0.76)	-0.067* (-1.89)	-0.034 (-0.88)	-0.243*** (-3.99)	-0.328*** (-4.91)	-0.400*** (-5.27)
$\text{Ln(R\&D)}_{t+1}$	0.186*** (12.01)	0.244*** (10.14)	0.248*** (8.29)	0.325*** (9.73)	0.340*** (8.18)	0.361*** (7.72)
Pressure	-0.016 (-0.37)	-0.017 (-0.39)	0.023 (0.48)	0.033 (0.30)	0.033 (0.34)	0.056 (0.50)
Adjusted R^2	0.797	0.823	0.860	0.662	0.714	0.775
Observations	20612	19844	19973	20612	19844	19973
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Peer Stock Price Informativeness, Mutual Fund Flow-driven Price Pressure and Innovative Efficiency.

We sort firms into tertiles based on the average *PIN* of peer firms, defined as firms in the same 3-digit SIC industry (Panel A) or firms in the same TNIC3 industry (Panel B) and estimate Model (4) in the three subsamples. The dependent variables are measures of future innovation output and the independent variable of interest is $Ln(R\&D)_{t+1} \times Pressure$. The following control variables are also included in the regressions: *Ln(Assets)*, *Leverage*, *CAPEX*, *Tangibility*, *ROA*, *Q*, *SA Index*, *Herfindahl*, and *Herfindahl*^{2}. Year fixed effects are also included. *t*-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Panel A: *PIN* of Peer Firms (SIC3)

Dependent Variables:	$Ln(Patent)_{t+2}$			$Ln(Citation)_{t+2}$		
Subsample:	High (1)	Medium (2)	Low (3)	High (4)	Medium (5)	Low (6)
$Ln(R\&D)_{t+1} \times$ Pressure	0.009	0.018	-0.053**	-0.018	-0.122	-0.313***
	(0.20)	(0.51)	(-2.25)	(-0.19)	(-1.58)	(-6.73)
$Ln(R\&D)_{t+1}$	0.240***	0.200***	0.191***	0.464***	0.369***	0.302***
	(10.26)	(11.83)	(9.17)	(9.92)	(10.65)	(9.05)
Pressure	0.033	0.002	0.057*	0.082	-0.082	0.151*
	(0.69)	(0.05)	(1.70)	(0.72)	(-0.71)	(1.84)
Adjusted R^2	0.832	0.853	0.848	0.745	0.749	0.730
Observations	25337	24791	24387	25337	24791	24387

Panel B: *PIN* of Peer Firms (TNIC3)

Dependent Variables:	$Ln(Patent)_{t+2}$			$Ln(Citation)_{t+2}$		
Subsample:	High (1)	Medium (2)	Low (3)	High (4)	Medium (5)	Low (6)
$Ln(R\&D)_{t+1} \times$ Pressure	0.004	-0.050	-0.057	-0.171	-0.253***	-0.300***
	(0.06)	(-1.32)	(-1.54)	(-1.15)	(-2.78)	(-4.30)
$Ln(R\&D)_{t+1}$	0.143***	0.138***	0.202***	0.278***	0.246***	0.306***
	(4.83)	(5.76)	(6.52)	(3.99)	(4.94)	(5.87)
Pressure	-0.013	0.095	0.002	-0.079	0.068	0.031
	(-0.17)	(1.51)	(0.04)	(-0.46)	(0.46)	(0.25)
Adjusted R^2	0.865	0.851	0.870	0.755	0.744	0.755
Observations	11794	11446	11446	11794	11446	11446
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Stock Performance Correlation With Peer Firms, Mutual Fund Flow-driven Price Pressure and Innovative Efficiency.

We sort firms into tertiles based on the firm's correlation with peer firms in terms of stock performance. Peer firms are defined as firms in the same 3-digit SIC industry or in the same TNIC3 industry. The dependent variables are measures of future innovation output and the independent variable of interest is $Ln(R\&D)_{t+1} \times Pressure$. The following control variables are also included in the regressions: *Ln(Assets)*, *Leverage*, *CAPEX*, *Tangibility*, *ROA*, *Q*, *SA Index*, *Herfindahl*, and *Herfindahl²*. Year fixed effects are also included. t-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Panel A: Return Correlation with Peer Firms (SIC3)

Dependent Variables:	$Ln(Patent)_{t+2}$			$Ln(Citation)_{t+2}$		
Subsample:	High (1)	Medium (2)	Low (3)	High (4)	Medium (5)	Low (6)
$Ln(R\&D)_{t+1} \times$ Pressure	-0.008	-0.061	-0.077	-0.252***	-0.417***	-0.395***
	(-0.31)	(-1.61)	(-1.60)	(-4.77)	(-5.63)	(-3.77)
$Ln(R\&D)_{t+1}$	0.240***	0.221***	0.207***	0.365***	0.339***	0.345***
	(12.19)	(9.95)	(8.49)	(10.35)	(8.08)	(7.78)
Pressure	0.038	-0.056	-0.025	0.227**	-0.199*	-0.058
	(0.93)	(-1.16)	(-0.47)	(2.39)	(-1.75)	(-0.44)
Adjusted R^2	0.834	0.817	0.820	0.722	0.703	0.699
Observations	22706	22143	22208	22706	22143	22208

Panel B: Return Correlation with Peer Firms (TNIC3)

Dependent Variables:	$Ln(Patent)_{t+2}$			$Ln(Citation)_{t+2}$		
Subsample:	High (1)	Medium (2)	Low (3)	High (4)	Medium (5)	Low (6)
$Ln(R\&D)_{t+1} \times$ Pressure	-0.022	-0.079**	-0.088	-0.267***	-0.447***	-0.419***
	(-0.74)	(-2.13)	(-1.60)	(-4.15)	(-5.47)	(-3.29)
$Ln(R\&D)_{t+1}$	0.172***	0.152***	0.180***	0.252***	0.219***	0.265***
	(6.97)	(4.22)	(5.05)	(5.32)	(3.42)	(4.43)
Pressure	0.044	-0.047	0.004	0.080	-0.046	-0.040
	(0.91)	(-0.79)	(0.07)	(0.69)	(-0.33)	(-0.26)
Adjusted R^2	0.863	0.853	0.840	0.733	0.719	0.702
Observations	12542	12183	12220	12542	12183	12220
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Financial Constraint, Mutual Fund Flow-driven Price Pressure and Innovative Efficiency.

In this table, we sort firms into tertiles based on *SA Index* (Panel A) or *WW Index* (Panel B) and estimate Model (4) in the three subsamples. The dependent variables are measures of future innovation output and the independent variable of interest is $Ln(R\&D)_{t+1} \times Pressure$. The following control variables are also included in the regressions: *Ln(Assets)*, *Leverage*, *CAPEX*, *Tangibility*, *ROA*, *Q*, *SA Index*, *Herfindahl*, and *Herfindahl²*. Year fixed effects are also included. *t*-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Panel A: Subsample Based on SA Index

Dependent Variables:	$Ln(Patent)_{t+2}$			$Ln(Citation)_{t+2}$		
Subsample:	High (1)	Medium (2)	Low (3)	High (4)	Medium (5)	Low (6)
$Ln(R\&D)_{t+1} \times$ Pressure	-0.049	-0.028	-0.049**	-0.175	-0.216***	-0.338***
	(-0.63)	(-0.98)	(-2.47)	(-0.97)	(-3.38)	(-8.97)
$Ln(R\&D)_{t+1}$	0.129***	0.164***	0.257***	0.277***	0.339***	0.403***
	(10.87)	(14.60)	(12.02)	(9.46)	(12.65)	(12.04)
Pressure	-0.006	-0.022	0.024	-0.184	-0.065	0.097
	(-0.09)	(-0.68)	(0.84)	(-1.01)	(-0.80)	(1.52)
Adjusted R^2	0.581	0.727	0.874	0.498	0.630	0.805
Observations	28689	27347	26713	28689	27347	26713

Panel B: Subsample Based on WW Index

Dependent Variables:	$Ln(Patent)_{t+2}$			$Ln(Citation)_{t+2}$		
Subsample:	High (1)	Medium (2)	Low (3)	High (4)	Medium (5)	Low (6)
$Ln(R\&D)_{t+1} \times$ Pressure	-0.012	-0.031	-0.053**	-0.080	-0.257***	-0.353***
	(-0.16)	(-1.03)	(-2.35)	(-0.48)	(-3.97)	(-8.53)
$Ln(R\&D)_{t+1}$	0.131***	0.188***	0.255***	0.259***	0.352***	0.378***
	(11.49)	(14.31)	(10.65)	(8.91)	(11.35)	(10.17)
Pressure	0.090	-0.041	0.022	0.173	-0.091	0.074
	(1.27)	(-1.22)	(0.72)	(0.93)	(-1.09)	(1.08)
Adjusted R^2	0.628	0.733	0.872	0.504	0.633	0.802
Observations	26741	25511	24934	26741	25511	24934
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Managerial Incentive, Mutual Fund Flow-driven Price Pressure and Innovative Efficiency.

In this table, we sort firms into tertiles based on CEO's *Wealth-Performance Sensitivity* and estimate Model (4) in the three subsamples. The dependent variables are measures of future innovation output and the independent variable of interest is $Ln(R\&D)_{t+1} \times Pressure$. The following control variables are also included in the regressions: *Ln(Assets)*, *Leverage*, *CAPEX*, *Tangibility*, *ROA*, *Q*, *SA Index*, *Herfindahl*, and *Herfindahl*^{2}. Year fixed effects are also included. t-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variables:	Ln(Patent)_{t+2}			$\text{Ln(Citation)}_{t+2}$		
Subsample:	High	Medium	Low	High	Medium	Low
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Ln(R\&D)}_{t+1} \times$ Pressure	-0.013	-0.054	-0.062	-0.297***	-0.331***	-0.286***
	(-0.35)	(-1.47)	(-1.39)	(-4.06)	(-4.67)	(-3.07)
$\text{Ln(R\&D)}_{t+1}$	0.120***	0.334***	0.226***	0.163**	0.502***	0.366***
	(3.04)	(8.08)	(6.43)	(2.48)	(7.29)	(4.97)
Pressure	-0.026	0.046	0.019	0.075	0.250	0.093
	(-0.49)	(0.72)	(0.28)	(0.62)	(1.64)	(0.60)
Adjusted R^2	0.904	0.889	0.868	0.830	0.812	0.790
Observations	6393	6177	5942	6393	6177	5942
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Blockholders, Mutual Fund Flow-driven Price Pressure and Innovative Efficiency.

In this table, we estimate Model (4) in the subsamples for firms with or without blockholders. The dependent variables are measures of future innovation output and the independent variable of interest is $Ln(R\&D)_{t+1} \times Pressure$. The following control variables are also included in the regressions: *Ln(Assets)*, *Leverage*, *CAPEX*, *Tangibility*, *ROA*, *Q*, *SA Index*, *Herfindahl*, and *Herfindahl*^{2}. Year fixed effects are also included. t-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variables:	Ln(Patent)_{t+2}		$\text{Ln(Citation)}_{t+2}$	
Subsample:	With	Without	With	Without
	(1)	(2)	(3)	(4)
$\text{Ln(R\&D)}_{t+1} \times$ Pressure	-0.059***	0.061	-0.367***	-0.130
	(-3.12)	(1.43)	(-10.29)	(-1.46)
$\text{Ln(R\&D)}_{t+1}$	0.218***	0.192***	0.341***	0.331***
	(17.35)	(8.97)	(14.83)	(9.20)
Pressure	-0.011	-0.071	0.051	-0.271*
	(-0.47)	(-1.16)	(0.95)	(-1.82)
Adjusted R^2	0.820	0.853	0.711	0.737
Observations	48204	34545	48204	34545
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table 10: Investor Horizon, Mutual Fund Flow-driven Price Pressure and Innovative Efficiency.

This table presents estimates from firm fixed effects regressions where the dependent variables are measures of future innovation output and the independent variable of interest is $Ln(R\&D)_{t+1}$ × *Pressure* × Short-Term Investor Ownership and $Ln(R\&D)_{t+1}$ × *Pressure* × Long-Term Investor Ownership. The following control variables are also included in the regressions: *Ln(Assets)*, *Leverage*, *CAPEX*, *Tangibility*, *ROA*, *Q*, *SA Index*, *Herfindahl*, and *Herfindahl*^{2}. Year fixed effects are also included. *t*-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variables:	$Ln(Patent)_{t+2}$ (1)	$Ln(Citation)_{t+2}$ (2)
$Ln(R\&D)_{t+1}$ × Pressure × Short-Term Investor Ownership	-0.106	0.145
	(-0.74)	(0.54)
$Ln(R\&D)_{t+1}$ × Pressure × Long-Term Investor Ownership	-0.203**	-0.819***
	(-2.02)	(-4.42)
$Ln(R\&D)_{t+1}$ × Pressure	0.065	0.098
	(1.29)	(0.96)
$Ln(R\&D)_{t+1}$	0.193***	0.492***
	(15.84)	(21.60)
Pressure × Short-Term Investor Ownership	0.065	0.099
	(0.36)	(0.23)
Pressure × Long-Term Investor Ownership	0.289**	1.003***
	(2.58)	(3.83)
$Ln(R\&D)_{t+1}$ × Short-Term Investor Ownership	0.057*	-0.055
	(1.72)	(-0.86)
$Ln(R\&D)_{t+1}$ × Long-Term Investor Ownership	0.038	-0.374***
	(1.63)	(-9.05)
Short-Term Investor Ownership	-0.122***	-0.116
	(-2.95)	(-1.18)
Long-Term Investor Ownership	-0.073**	0.223***
	(-2.47)	(3.61)
Pressure	-0.028	-0.110
	(-0.57)	(-0.93)
Adjusted R^2	0.823	0.711
Observations	82749	82749
Firm Controls	Yes	Yes
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

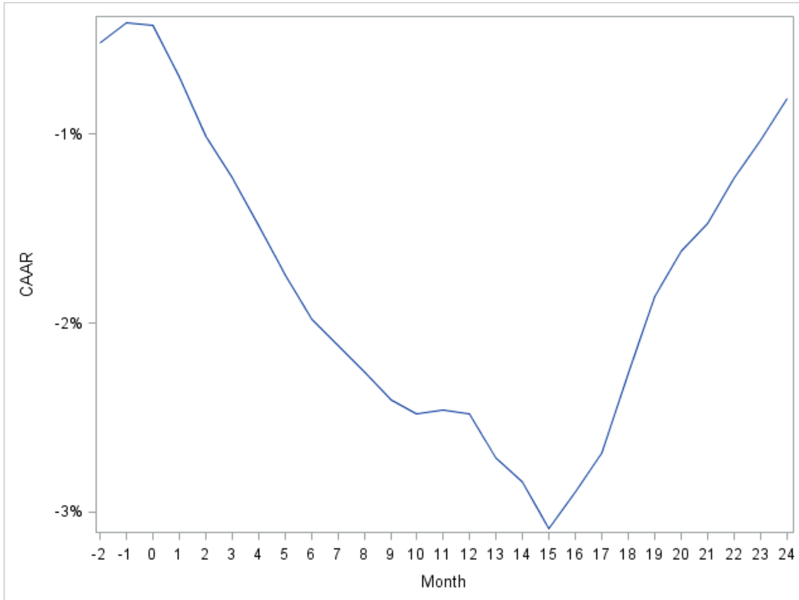


Figure 1: CAR after Fire Sale
In this figure, we present the three-month moving average of cumulative abnormal return of stocks after mutual fund flow-driven sale.

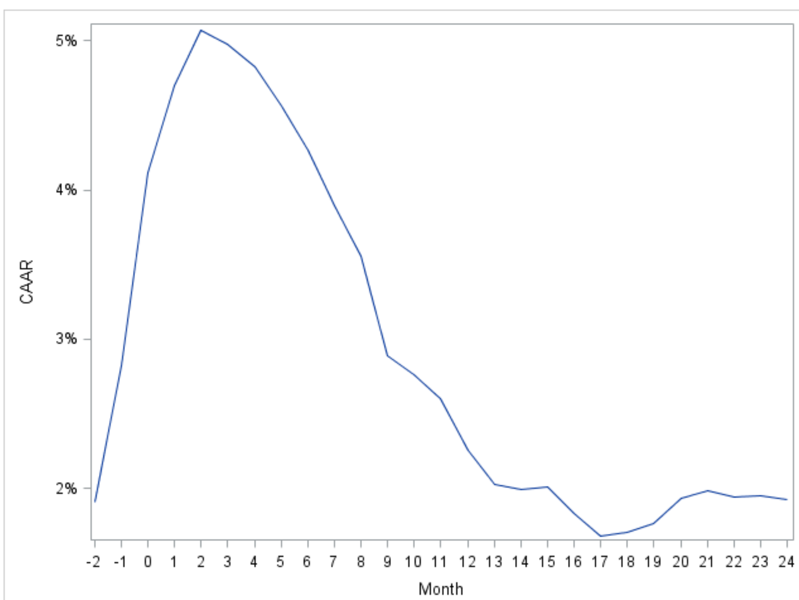


Figure 2: CAR after Fire Purchase
In this figure, we present the three-month moving average of cumulative abnormal return of stocks after mutual fund flow-driven purchase.

CHAPTER II

INTELLECTUAL PROPERTY PROTECTION AND FINANCIAL MARKETS: PATENTING VS. SECRECY

2.1 Introduction

Intellectual property (IP), whether in the form of patents or confidential information about customers or production processes, is the source of much of the value created by firms. This is particularly the case in advanced economies where innovation and the production of IP are substantial drivers of economic growth. The manner in which IP is protected and innovators rewarded for their creations remains a matter of debate. After a new product or process is discovered, its inventor can decide to keep the invention secret, with the risk of it being developed elsewhere or surreptitiously copied. Alternatively, patent protection can be sought and the invention disclosed. Patents can be regarded as a contract between society and the inventor: society benefits from the disclosure and the inventor obtain exclusive rights over the technology for a period of time.[1] Whether firms choose to patent or to keep their inventions secret will depend on factors such as the extent to which patent rights are enforced, the costs of firm opacity and of maintaining secrets. In the paper we study the trade-offs patenting firms make in terms of disclosure and patenting decisions. In particular, we study the effect of exogenous events that shift the trade-off between alternative modes of IP protection. We develop and test hypotheses with regard to the impact on firms' patenting propensity, their financing policies and various attributes such as

[1] The patent protection period in the US is now 20 years from the filing date of the patent application as a result of legislation to implement WTO agreements. Historically, patents were disclosed publicly only after they had been granted. This has changed, however, and the requirement under the American Inventors Protection Act of 1998 is that patent applications be disclosed to public 18 months after the filing date.

its stock liquidity.

Protecting intellectual property can be costly and both modes – patenting and secrecy – have their drawbacks. Even when a firm can receive a patent for its invention, it faces the cost of renewing its patent and the threat of litigation. The disclosure that the patent requires can also leave the firm vulnerable to imitation or inventing around the patent by its competitors. Keeping a discovery secret provides a form of IP for many firms that either choose not to or cannot patent their discoveries. Interestingly, surveys suggest that in many industries secrecy is considered more important than patents as a means of protecting IP (Scherer, et al., 1959; Taylor and Silberston, 1973; Mansfield, 1986; Levin, et al., 1987; Cohen, Nelson and Walsh, 2000). Trade secrets, by way of contrast to patents, must be held in confidence if they are to be protected. The nature of trade secret protection is also narrower. A firm can only sue for trade secret theft someone who misappropriated its idea, not someone who made the same discovery independently. Consistent with this suggestion, Lerner (1995) finds that small firms are much less likely to patent in subclasses where large firms and those with extensive litigation experience have already patented. Friedman, Landes, and Posner (1991) suggest that firms may employ trade secrecy because it is more cost-effective than seeking formal protection. Firms that innovate infrequently may consequently eschew these forms of protection, and rely instead on trade secrecy.

The level of patent protection will affect a firm's decision on whether (or not) to patent and, hence, whether (or not) to disclose its technological progress. To the extent this affects the information available to outside investors this may also affect the cost of equity capital. For innovative firms, information asymmetry between insiders and outside investors tends to be higher because it is more difficult for the outsiders to value R&D investments compared to ordinary investments (Leland and Pyle, 1977). This can lead to a greater adverse selection cost in stock market trading, giving rise to lower stock liquidity and higher cost of capital for patenting firms

(Amihud and Mendelson, 1986; Amihud, 2002; Easley and O'Hara, 2003). A number of studies in the literature have documented the informational role of patent grants in financing. For example, through interviews with a variety of practitioners and investors in the software industry, Mann (2005) finds that venture capitalists often take into account the information from patents of the portfolio firms in making their investment decisions. Moreover, Kogan, Papanikolaou, Seru, and Stoffman (2012) use stock market reaction to news about patents to assess the economic value of innovations, suggesting that patent grants do provide new information to the stock market.

We hypothesize that strong patent rights protection would be expected to encourage firm to increase patenting and, consequently, reduce information asymmetry.[2] Further, the reduction in information asymmetry on the patenting would lead to firm's stock becoming more liquid. We expect the greater liquidity to attract more institutional investors and, in turn, more accurate analyst forecast. The firms that benefit from an increase in liquidity may be more willing to raise capital in the form of equity financing. Smaller firms with lower market share, that may have been unwilling to litigate to protect their patents in the past, are likely to be the firms that are more strongly affected by the strengthening of patent protection.

IP protection can also be strengthened by giving firms greater ability to sue for the disclosure or misuse of a firm's confidential information. Interestingly, the implications of strengthening of trade secrecy protection are quite the reverse of greater protection of patents. In particular, we might expect firms to pull back on their patenting (even if there is no drop off in the level of innovation). They may also be more reluctant to releases other types of information. The overall effect will be to reduce their liquidity. The greater opacity as a result of a greater reliance on secrecy

[2]Given the lower cost of disclosing information overall, firms can also choose to disclose information in other ways, such as voluntary earnings forecast which will be discussed in later section.

could reduce the extent to which the firm is followed by analysts and held by institutional investors. However, because this the result of firms optimally choosing to reduce information disclosure, we would not usually expect there to be a drop in firm value or in the extent of innovation R&D expenses.

To test our hypotheses, we exploit two sets of natural experiments created by the passage of laws or their implementation. The first is the increased protection that was provided to trade secrets across different states over a number of years. Since these changes occurred at different points in time, this allows us to identify the effect of these changes on firm financing and transparency. The second major exogenous change we study is the implementation of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS). This had the effect of providing significantly greater intellectual protection to patents across the globe.

However, before turning to these two natural experiments, we examine an illustrative case: that of the effect of patent protection in the context of a particular industry, semiconductor manufacturing. The interesting feature of this industry, as documented by Hall and Ziedonis (2001) is that this was an industry that tended to rely largely on trade secrecy, but moved over time to a much greater usage of patents to protect IP. This change occurred in the late 1980s and 1990s on account of events such as the establishment of a centralized Court of Appeals that favored stronger patent protection and the resolution of a certain influential cases. Consistent with our hypotheses, we show that this shift toward patenting in the semiconductor industry was accompanied by a substantial increase in liquidity of the stocks of the industry firms. Our control group here is the chemical-pharmaceutical industry that exhibited relatively little change in its patenting activity and the liquidity of its firms' stocks.

We first examine the implication of trade secret protection to stock liquidity. Using the staggered enactment of trade secret statute to exploit the exogenous variation in trade secret protection, we find that stronger trade secret protection causes lower stock liquidity. Furthermore, we find that stronger trade secret protection is related to lower analyst forecast quality in terms of dispersion and accuracy, suggesting that trade secret protection encourage more secrecy and thus increases information asymmetry and reduces stock liquidity.

We further find that trade secrets protection has a greater effect on small firms. Small firms in terms of total assets or market share reduced patenting after the enactment of trade secret statue, indicating that they substituted trade secrets for patenting. Meanwhile, small firms experience greater decrease in stock liquidity compared to larger firms with stronger trade secrets protection. As small firms are more reliant on secrecy for protecting their IP (Friedman, Landes, and Posner, 1991; Lerner, 1995), stronger trade secret protection results in greater increase in information asymmetry and drop in stock liquidity among small firms.

Lower stock liquidity can induce financing friction by increasing cost of equity capital (Amihud and Mendelson, 1986; Amihud, 2002; Easley and O'Hara, 2003). Our analysis suggests that this is the case when trade secrets statute is introduced. We find that small firms are more likely to raise equity capital after stronger trade secrets protection, possibly due to better investment opportunity with stronger trade secret protection. However, we show that seasoned equity offerings (SEO) after the enactment of trade secret statute received more negative stock market reaction, suggesting that raising equity capital become more costly after the enactment of trade secrets statute. Overall, we find that stronger trade secrets protection impede financing by causing more information asymmetry in the stock market and reducing stock liquidity.

Next, we exploit an exogenous change in patent protection caused by the implementation of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) and its impact on firm's stock liquidity and equity finance by exploiting.

Using difference-in-differences approach, we find that an exogenous increase in the level of patent rights protection due to TRIPS enhances stock liquidity for patenting firms. The effect is economically significant. For example, in a three-year period surrounding the effective day of TRIPS implementation in the US, the bid-ask spread of treatment firms who had applied for patents in 1993 or 1994 (treatment group) decreased by 5.1%, while that of the matched control group has no significant change during the same period. Supporting the idea that increased patenting reduces information asymmetry, we find that patenting firms have better information environment in terms of lower analysts' forecast dispersion and error after TRIPS.

To distinguish the causal effect of TRIPS on stock liquidity from other confounding events, we examine the heterogeneity of the effect among treatment firms. We find that the effect is greater for firms in industries with higher reliance on export, consistent with the fact that TRIPS is designed to protect intellectual property in international trade. We also show that industries that find trade secret less effective are more affected by TRIPS in terms of stock liquidity, suggesting that firms benefit more from TRIPS where there is no effective alternative to patenting.

Moreover, we find that among patenting firms, small firms in terms of total assets or market share, as well as financially constrained firms in terms of access to public debt or dividend policy, experienced greater increase in stock liquidity compared to large firms around the implementation of TRIPS. These firms are more likely to raise equity capital after TRIPS. Meanwhile, SEOs after TRIPS receive better market reaction. These findings are supportive of the prediction that patent protection is more important for small firms and patent protection helps reduce financing friction.

This paper contributes to the emerging literature on finance and innovation (Hall and Lerner, 2009). There is a growing number of studies on the influence of different types of financing arrangement to corporate innovation (e.g. Atanassov, Nanda, and Seru, 2007; Chava, Oettl, Subramanian, and Subramanian, 2012; Chava, Nanda, and

Xiao, 2013; Tian and Wang, 2011; etc.). Our paper, by contrast, studies how legal protection of intellectual property affects firms' financing. We find that while stronger secrecy protection reduces stock liquidity and impedes financing, stronger patent protection facilitates firms' equity financing by improving stock liquidity. Easier access to capital allows firms to invest more on innovative activities and enhance productivity. Bena and Garlappi (2012) show that imperfect competition in innovation causes laggard firms to have higher cost of capital. Our paper complements their study by showing that stronger IPR protection benefits small (and possibly laggard) firms more in improving their stock liquidity and reducing cost of capital. Our paper is also supportive of the notion that stock liquidity is endogenously determined given the cost and benefit (Balakrishnan, Billings, Kelly, and Ljungqvist, 2013; Dass, Nanda, and Xiao, 2013). As is shown in our paper, when patent protection improves, cost of maintaining high stock liquidity decreases and stock liquidity increases in equilibrium.

Our paper also adds to the literature on intellectual property.[3] The enforcement of intellectual property protection is shown to contribute to economic growth (Gould and Gruben, 1996; Park and Ginarte, 1997; Falvey, Foster, and Greenaway, 2006). Potential mechanisms that has been discussed in the literature includes the effect of IPR protection on future innovation and R&D strategy (Taylor, 1994; Zhao, 2006; Lerner, 2009), technology transfer (Branstetter, Fisman, and Foley, 2006), international trade (Maskus and Penubarti, 1995), and foreign direct investment (Lee and Mansfield, 1996; Glass and Saggi, 2002), etc. A few studies examine the implication of intellectual property protection to financing. Mann (2005) discusses the role of patent in financing in the software industry. He finds evidence that venture capitalists take into account the value of patents a portfolio firm holds when investing. Sichelman and Graham (2010) conduct a large survey among startups and find that

[3]Please refer to Jaffe (2000), Gallini (2002), and Ziedonis (2010) for comprehensive survey of the literature on intellectual property right.

many firms rely on patents to improve the chance of financing. Hsu and Ziedonis (2008) study venture-backed semiconductor firms and find that patenting is associated with higher funding-round valuations. All these papers suggest the importance of patents in raising venture capital.

To the best of our knowledge, our paper is the first to empirically study the implications of intellectual property protection to equity financing for public firms. This is an important question not only because equity financing plays an more important role for innovative public firms, but also innovative firms face greater challenge in equity financing due to information asymmetry regarding innovative activities. Our findings provide policy makers and academic researchers with a new perspective for the discussion and future development of IP protection law.

2.2 IP Protection: Natural Experiments

We discuss the two exogenous shifts that occurred in IP protection that we exploit to test our hypotheses: (i) The greater protection of trade secrecy that took place over the years in various US states; (ii) The passage of the TRIPS, with the greater global protection provided to patents. We begin, however, by discussing the illustrative case of the semiconductor manufacturing industry, that experienced a large shift from reliance on secrecy to patenting over the course of the 1990s.

2.2.1 An Illustrative Case: Semiconductor Industry Shift from Secrecy to Patenting

Hall and Ziedonis (2001) discusses why the rise in patents during the 1990s may reflect, to some extent, an increase in the propensity to patent due to patent reform – even if the policy changes did not necessarily enhance the development of these inventions. They find support for their conjecture in the semiconductor industry, based on data from 110 semiconductor firms during 1975 to 1996, and interviews with managers and executives. Due to the short product life cycles and the fast pace of technological change, semiconductor firms had relied heavily on secrecy and lead time instead of patents to protect their intellectual property. This changed over time on account of the creation of the centralized Court of Appeals. By enforcing patents more strongly, Hall and Ziedonis argue, the court incentivized inventors to extract royalties from prospective infringers by litigation. There were also important "demonstration effects" associated with the successful patent litigation of Texas Instruments and Polaroid in 1985 and 1986.

We present the greater reliance on patenting in the semi-conductor industry in Figure 3. Our comparison industry here is the patenting per firm done by Chemical -Pharmaceutical industry. The Chemical-Pharmaceutical industry has long relied more on patenting than secrecy, as has been noted in various cross-industry surveys []. The reason has to do with the ability to characterize the new produce (or "molecule") better than in many other industries. As we see, there is little change over time in the per-firm patenting activity in this industry compared to the substantial increase in patenting by the semiconductor firms.

In Figure 4 we present the levels of stock illiquidity of the firms in these two industries. As can be seen, there is reactively little change in the liquidity, as indicated by Amihud-Mendelson and Turnover measures, of the stocks in the Chemical-Pharmaceutical industry. There is, however, a substantial improvement in the liquidity of the semi-conductor industry firms over this time. Observe that the liquidity appears to track well the increase in patent grants in the industry. Regression results that relate firm-level liquidity to patent grants over this time are consistent with the graphical patterns.[4]

Overall, we consider the pattern to be supportive of our hypotheses. However, the changes took place gradually over time as the patents became more attractive for the semi-conductor industry. We will now turn to exogenous shifts in the costs and

[4]The regression results are unreported for brevity and are available upon request.

benefits in the firm of IP protection that are more sharply defined in terms of when the events occurred. The greater time specificity in terms of the events has the benefit of reducing possible uncertainty in terms relating the changes to the exogenous shifts.

2.2.2 Trade Secrets Law

Trade secrets in the US have historically been protected by common law. In 1979, the National Conference of Commissioners on Uniform State Laws published the Uniform Trade Secrets Act (UTSA), which provides a comprehensive statute on trade secrets protection for enactment by the states.[5] The UTSA improves the trade secret protection in three aspects: substantive law, procedures, and remedies (Png, 2014). As each state has different level of trade secrets protection under common law and state trade secrets statute improves the protection to different extent, Png (2014) compiles an index specifying six items that characterize the three aspects of trade secrets protection under UTSA:

- *Substantive law:*
  - *Whether a trade secret must be in continuous business use;*
  - *Whether the owner must take reasonable efforts to protect the secret;*
  - *Whether mere acquisition of the secret is misappropriation;*
- *Civil procedure: The limitation on the time for the owner to take legal action for misappropriation;*
- *Remedies:*
  - *Whether an injunction is limited to eliminating the advantage from misappropriation;*
  - *The multiple of actual damages available in punitive damages.*

[5] "Uniform Trade Secrets Act Prefatory Note", *Uniform Laws Annotated*, Vol. 14.

Table 11 shows the year of enactment of trade secrets statute in each state, the index that Png (2014) develops to measure the strength of trade secrets protection in each state prior to the enactment of statute and the improvement in trade secrets protection given by the statute. The index ranges from 0 to 1, with each increment of 1/6 representing one more item included in the trade secret protection. Details on the construction of the index is in the Appendix. According to Png (2014), there are 39 states that adopted trade secrets statute from 1980 to 2000. The enactment of trade secret statute is concentrated in the 1980s. Specifically, twelve states enacted the statute from 1980 to 1985 and twenty one states enacted from 1986 to 1990. We use this staggered enactment of trade secret statute as an exogenous shock to the protection of trade secret and examine its impact on firms' information asymmetry and stock liquidity.

2.2.3 TRIPS

Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) was negotiated at the end of Uruguay Round of the General Agreement on Tariffs and Trade (GATT) in 1994. The purpose is to enforce a global standard of intellectual property right protection among fellow WTO members in order to facilitate technology transfer and technological innovation.[6] The agreement requires member states to implement laws that enforce patent protection for at least 20 years .

An important principle of the agreement is national treatment. According to the agreement, " Each Member shall accord to the nationals of other Members treatment no less favorable than that it accords to its own nationals with regard to the protection of intellectual property". With the implementation of TRIPS, patents granted in the U.S. will receive patent protection in other WTO member countries. This ensures that firms can have exclusive right to profit from their technology products in international

[6]The objective and basic principles of TRIPS is stated in the Annex 1C of the WTO agreement `http://www.wto.org/english/docs_e/legal_e/27-trips_03_e.htm`.

trade.

Though patent protection law was in place in the U.S. prior to TRIPS, the implementation of TRIPS in the U.S. also strengthened patent protection domestically. The Uruguay Round Agreements Act (URAA) enacted on December 8th, 1994 enforces the twenty-year patent term in accordance with TRIPS. Prior to the enactment, the patent term in the U.S. was seventeen years from the day the patent issued. After the enactment, patents filed on or after June 8th, 1995 are granted for a term from the issuance date to twenty years from the date of filing. [7] Therefore, patents granted after the law change would receive an extended term as long as the patent processing time is less than 3 years.

Therefore, the implementation of TRIPS in the U.S. and other WTO member countries strengthen patent protection on two dimensions: One by increasing the patent term and second by streamlining and providing more protection and enforcement of patent rights internationally. With the stronger patent protection, patenting firms that use patent will have lower cost of disclosing information on their innovations and further improve stock liquidity by reducing information asymmetry. While TRIPS is implemented gradually through the transition period, the enactment and implementation of URAA in U.S. has more definite timing. We therefore define post law change indicator based on the date when the twenty-year patent term is enforced (June 8th, 1995).

We believe that these two events are exogenous to stock liquidity since the motivation of trade secrets statutes and TRIPS is not related to the stock market or equity financing. Therefore, the two law changes regarding IP protection should provide valid natural experiment for testing our hypothesis.

[7] http://www.uspto.gov/web/offices/pac/mpep/s2701.html

2.3 Data

We extract patent data from NBER patent database. The NBER patent database provides information on patents granted from 1962 to 2006.[8] We use the assignee-GVKEY link provided by the NBER database to match the patent data to firms' accounting information and stock price information from Compustat and CRSP, respectively. We also use analyst forecast data from I/B/E/S. We include common stock (Share Code 10 or 11) traded in New York Stock Exchange, American Stock Exchange, or Nasdaq (Exchange Code 1-3) and exclude firms with total assets less than 5 million dollars.

2.3.1 Stock Liquidity

In this paper, our main variable of interest is stock liquidity. A stock is generally considered liquid if it can be traded readily without impacting the stock price and/or the trading cost is low. High stock liquidity has been shown to be related to lower cost of equity (Amihud and Mendelson, 1986; Amihud, 2002) as investors demand lower return given the the lower trading cost. Therefore, stock liquidity is generally a desirable feature for firms, especially those need to raise capital from the equity market. While there is a large body of literature studying the determinants of stock liquidity (see Easley and O'Hara, 2003), it generally reflects two types of costs. One is the adverse selection cost due to information asymmetry among market participants and the other is the transaction cost. An improvement in IP protection for patent or trade secret has different implications to the information environment of the firm, thus may have different impact to stock liquidity. Given the link between stock liquidity and cost of equity capital, we focus on stock liquidity as the outcome variable in our empirical analyses.

We use three measures of stock *illiquidity.* The first measure is Amihud's (2002)

[8] A detailed description of these data can be found in Hall, Jaffe, and Trajtenberg (2001)

illiquidity ratio (*Ln(Amihud)*). It is defined as $ln(AvgILLIQ \times 10^9)$, where $AvgILLIQ$ is an yearly average of illiquidity, which is measured as the absolute return divided by dollar trading volume:

$$AvgILLIQ_{i,t} = \frac{1}{Days_{i,t}} \sum_{d=1}^{Days_{i,t}} \frac{|R_{i,t,d}|}{DolVol_{i,t,d}}.$$

where $Days_{i,t}$ is the number of valid observation days for stock i in fiscal year t, and $R_{i,t,d}$ and $DolVol_{i,t,d}$ are the daily return and daily dollar trading volume, respectively, for stock i on day d of fiscal year t. This measure reflects the average stock price sensitivity to one dollar trading volume. Higher $AvgILLIQ$ is interpreted as lower stock liquidity.

The second measure is the yearly average of daily bid-ask spread:

$$\text{Ln(Bid-Ask Spread)}_{i,t} = ln(\frac{1}{Days_{i,t}} \sum_{d=1}^{Days_{i,t}} \frac{Ask_{i,t,d} - Bid_{i,t,d}}{(Ask_{i,t,d} + Bid_{i,t,d})/2}),$$

where $Days_{i,t}$ is the number of valid observation days for stock i in fiscal year t, and $Ask_{i,t,d}$ and $Bid_{i,t,d}$ are the closing ask and bid prices of stock i on day d of fiscal year t. Higher *Bid-Ask Spread* is interpreted as lower stock liquidity. We do not use this measure for the empirical analysis of trade secrets law due to the limited data availability of bid/ask prices in the 1980s.

The third measure of illiquidity is the *negative* yearly average of daily trading turnover, which is calculated as:

$$-Ln(Turnover)_{i,t} = -ln(\frac{1}{Days_{i,t}} \sum_{d=1}^{Days_{i,t}} \frac{Vol_{i,t,d}}{Shrout_{i,t,d}}),$$

where $Vol_{i,t,d}$ and $Shrout_{i,t,d}$ are the shares traded and number of shares outstanding of firm i in day d of fiscal year t. Higher trading volume generally reflect higher stock liquidity. To be consistent with the other two measures, we use the negative value of turnover so that it measures the stock's illiquidity instead of liquidity.

2.4 Empirical Design

We test the impact of trade secret statute on stock liquidity using the following model:

$$\text{Stock Illiquidity}_{i,t} = \alpha_1 + \beta_1 \text{TS Law}_{s,t} + \gamma_1' CONTROL_{i,t-1} + \phi_i + \theta_t + \epsilon_{i,t}. \quad (5)$$

TS Law is the index representing the strength of trade secret protection for state s in year t shown in Table 12. Firm fixed effects (ϕ_i) are year fixed effects (θ_t) are also included in the model to control for factors invariant over time or across firms in the same year. For stock illiquid we use two empirical proxies: *Ln(Amihud)* and *-Ln(Turnover)*. We control for a set of firm and industry characteristics lagged by one year that has been shown in the literature to be related to stock liquidity, including *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Tangibility*, *Cash*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*.[9] We perform this test for public firms from 1980 to 2000 since most of the trade secret statutes are enacted in the 1980s and early 1990s. We do not use *Ln(Bid-Ask Spread)* in this test due to poor data availability of bid and ask prices in the 1980s. The prediction is that β_1 is significantly positive if stronger trade secret protection reduces transparency of firms and thus increases stock illiquidity. Panel A of Table 12 presents summary statistics for all the variables used in the analyses of trade secret and stock liquidity.

To test the effect of TRIPS on stock liquidity, we estimate the following difference-in-differences model:

$$\text{Stock Illiquidity}_{i,t} = \alpha_1 + \beta_1 \text{Post}_{i,t} + \beta_2 \text{Post}_{i,t} \times \text{Treated}_i + \gamma_1' CONTROL_{i,t-1} + \phi_i + \epsilon_{i,t}. \quad (6)$$

When estimating this model around TRIPS, $Post_{i,t}$ is a binary variable that equal to 1 if the observation is after the effective date when the twenty-year patent term is enforced (June 8th, 1995) and 0 otherwise. $Treated_i$ is the treated group indicator that identifies firms affected by TRIPS. A firm is categorized as treated firm if it had

[9] All the variables are defined in the appendix.

applied for patents from 1993 to 1994, the two-year period prior to the implementation of TRIPS in the U.S.[10] In addition, we control for the same set of control variables as in Model 5 as well as firm fixed effects (ϕ_i) to control for all the time invariant firm characteristics. Our prediction is that β_2 should be significantly negative if patenting firms reduce stock illiquidity significantly more than nonpatenting firms because of the legislative change in patent protection.

We match every treated firm with one control firm that is not affected by the change in patent law. We categorize a firm as a candidate control firm if it has not applied for any patents from 1993 to 1994. We note that it is possible that firms that did not use patent may pursue it after the new patent law motivated by the strengthened patent protection. Also it is likely that firms never use patent may also benefit from TRIPS through its strengthening protection of other forms of intellectual property such as copyright and trademark. Nevertheless, these possibilities should bias against finding significant difference between treated firms and control firms.

Firms are matched based on the characteristics mentioned above prior to the effective date of TRIPS in the U.S. using propensity score matching with 0.005 caliper. The probit model estimates used for computing propensity score are presented in Table 23. Column 2 shows that after matching, most of the firm characteristics are not significantly different between the treated group and control group. In Panel B of Table 12, we present summary statistics for the treated group and the matched control group in the 7-year period around the implementation of TRIPS in the U.S. Most of the variables are very close between the two groups. The mean number of patent grants for the control group is close but not equal to zero, implying that firms that did not apply for patents within two years prior to TRIPS may have patents granted some time during the seven year period. As we have discussed, having control

[10]We use a two-year period because the typical processing time of patent applications is about 2 years. So firms that applied for patents in 1993 or 1994 are likely to have patents granted after the enforcement date of TRIPS.

firms that may be affected by TRIPS should bias against our prediction.

2.5 Empirical Results

2.5.1 Trade Secret Law

2.5.1.1 Trade Secret Statutes and Stock Liquidity

Columns 1 and 4 of Table 13 present the estimates of Model (5). The estimate of β_1 is positive for both *Ln(Amihud)* and *-Ln(Turnover)* as dependent variable, suggesting that stock illiquidity is higher after the enactment of trade secret law in the firm's headquarter state. The estimate, however, is only significant for *-Ln(Turnover)*. Based on the coefficient estimate, an average increase in trade secret protection by the enactment of statute (0.44 increase in the index) is related to 4.8% decrease in both *Ln(Amihud)* and *-Ln(Turnover)*.

The impact of trade secret law may vary across firms depending on their reliance on trade secret to protect intellectual property. Small firms are generally more reliant on trade secrets because it is costly to seek formal IP protection (Friedman, Landes, and Posner, 1991; Lerner, 1995). Greater trade secret protection may induce small firms to use more trade secret and thus cause their stock to be less liquid. To test this hypothesis, we reestimate Model 5 and interact *TS Law* with indicator of firms whose total assets or market share below the sample median. We present the results in column 2, 3, 5, and 6 of Table 13, which show that the effect of trade secret statute on stock liquidity is concentrated among small firms. The coefficient on the interaction term is strongly significant for both firms with low total assets or firms with low market share. The economic significance is also substantial. For example, for firms with below-median total assets, an average increase in trade secret protection by the enactment of statute is related to a 44.5% decrease in *Ln(Amihud)* and 10.3% decrease in *-Ln(Turnover)*. This test result is consistent with out prediction that small firms, who potentially benefit more from stronger trade secret protection, increase stock liquidity more after the enactment of trade secret statute.

Lower stock liquidity is likely driven by higher adverse selection cost when firms adopt more trade secret. To test whether information asymmetry increase around the enactment of trade secret statute, we test a model similar to Model 5 but replace the stock illiquidity measures with measures of analyst forecast quality as the dependent variable. Specifically, we focus on analyst forecast dispersion and analyst forecast error as measures of analyst forecast quality. Analyst dispersion is measured by the standard deviation of analyst's forecasts divided by analysts' median forecast and analysts' forecast error is measured by the absolute difference between analysts' median forecast and actual earnings divided by actual earnings. Both are measured in percentage and we take natural logarithm of one plus these measures as dependent variables in our regression. The results presented in Table 14 show that analysts' forecast dispersion and error increase after the enactment of trade secret statute. An average increase in trade secret protection by the enactment of statute is related to 7.7% (9.8%) increase in analysts' forecast dispersion (error). However, the effect is mostly similar between large firms and small firms, except for firms with low market share that have marginally greater increase in analyst forecast dispersion. This result is supportive of the hypothesis that information asymmetry increases after firms enjoy stronger trade secret protection.

2.5.1.2 *Trade Secret Protection and Patenting Activity*

Png (2014) shows that technological firms increase R&D expenditure after the enactment of trade secret statute, suggesting that stronger trade secret protection encourages more investment in innovative activities. In the previous section we find that small firms experience greater decrease in stock liquidity. The ground of our prediction is that small firms are more likely to switch from patenting to secrecy after the strengthening of trade secret protection. We therefore test whether small firms indeed reduce patenting after the enactment of trade secret statute. In Table 15, we present the estimation of a model where the dependent variable is the log number of patent applications and the independent variable of interest is *TS Law* and the interaction with small firm indicators. The first column shows the estimates without the interaction and the coefficient on *TS Law* is significantly negative at 10%, suggesting that on average firms reduce patenting after the enactment of trade secret law. The estimated coefficient on the interaction term presented in column 2 and 3 are significantly negative and greater in magnitude than the estimate in column 1. This indicates that it is mainly small firms that reduce patenting after stronger trade secret law. This is again consistent with our hypothesis that small firms rely more on trade secret after the statute, causing greater opaqueness and lower stock liquidity.

2.5.1.3 Trade Secret Protection and Equity Financing

Stock liquidity is a important determinant of firm value (Fang, Noe, and Tice, 2009). One of the reason is because higher stock liquidity facilitates equity financing (Amihud and Mendelson, 1986; Amihud, 2002; Easley and O'Hara, 2003, Butler, Grullon, and Weston, 2005). Greater trade secrets protection may enhance the value of R&D investment, causing firms to seek for more external capital. On the other hand, lower liquidity due to greater use of secrecy may constrain firms' equity financing. We therefore examine firms' equity financing activity after trade secret statute is effective and the market reaction when firms raise equity capital.

We first estimate the following model to test how trade secret law changes the likelihood of SEO:

$$\Pr(\text{SEO})_{i,t} = \alpha_1 + \beta_1 \text{Trade Secret Law}_{i,t} + \gamma_1' CONTROL_{i,t-1} + \phi_i + \theta_t + \epsilon_{i,t}, \quad (7)$$

where the dependent variable is the likelihood of firm i issuing an SEO in year t. Similar to Model 5, we control for the same set of firm characteristics as well as firm and year fixed effects. This model is estimated using conditional logit regression. Column 1 of Table 16 shows the estimates. The coefficient of β_1 is not significant, suggesting that firms on average are not more likely to issue SEO after trade secret statute. To show how the effect differ for small firms, we add an interaction between *TS Law* and indicators of small firms in column 2 and 3. The results show that firms with lower total assets or market share are significantly more likely to issue SEO after trade secret statute. This result indicates small firms do have higher demand for equity capital, possibly due to the better investment opportunities given stronger trade secret protection.

So far we find that small firms are more likely to raise equity capital despite lower stock liquidity after the enactment of trade secret statute, the next question is how the stock market reacts to SEOs after trade secret statutes. We test the following model for all the SEO incidences:

$$\text{SEO CAR} = \alpha_1 + \beta_1 \text{Trade Secret Law}_{i,t} + \gamma_1' CONTROL_{i,t-1} + \lambda_s + \theta_t + \epsilon_{i,t}, \quad (8)$$

where *SEO CAR* is the cumulative abnormal return (CAR) over the equal-weight market return over various horizons. λ_s is the fixed effect for state s and θ_t is the fixed effect for year t. In Table 17 we present estimates for CARs computed over four different horizons. Except for the three-day CAR around SEO announcement, all the other CARs over longer horizon are significantly lower for SEOs after trade secrets statute. Based on estimates in column 4, an average increase in trade secrets protection after trade secrets statute is associated with 7.5% lower abnormal return over one year. This finding is suggestive that stronger protection on secrecy likely induce financing friction by increasing information asymmetry and lower stock liquidity.[11]

[11]Note that we do not find stronger effect of trade secret law on SEO CAR for small firms. This is likely the outcome when firms make their optimal SEO decisions in equilibrium.

2.5.2 TRIPS

2.5.2.1 TRIPS and Stock Liquidity

In this section, we focus on TRIPS as another natural experiment and examine the implication of stronger patent protection on firms' stock liquidity and financing. We follow the similar structure as the analyses of trade secrets law by examining TRIPS and stock liquidity first, followed by testing the heterogeneity of the effect TRIPS, then studying the implication to equity financing.

The hypothesized mechanism is that stronger patent protection encourages greater reliance on patenting to protect firms' IP, making the firm more transparent and increasing stock liquidity. Figure 5 shows that patenting activity indeed increases after TRIPS. The average number of patent applications of the public firms increases in the year U.S. enacted law complying with TRIPS. Since on average application-grant lag is two years during that period (Hall, Jaffe, and Trajtenberg, 2001), the number of patent grants increases sharply in the third year after TRIPS. Prior to 1998, patent-related information becomes public when the patents are granted (Kogan, Papanikolaou, Seru, and Stoffman, 2012). Therefore, we expect the increase in stock liquidity to take place as a bulk of patents are granted and focus on a seven-year window around TRIPS in our empirical tests.

We start with testing the impact of TRIPS on stock liquidity. As mentioned in Section 2.4, we estimate a difference-in-differences model specified in Equation (6). We categorize a firm as a treated firm if it applied for patents in the two-year period prior to the implementation of TRIPS and we match every treated firm with one control firm.

Table 18 presents estimates of the diff-in-diff models around TRIPS. In columns 1, 3, and 5 we present estimates from year t-1 to year t+1 surrounding the implementation of TRIPS in the U.S., while in columns 2, 4, and 6 we present that from year t-3 to year t+3. The results show that the coefficient for the interaction term is significantly negative at 1% level for all measures of stock illiquidity and all alternative time window. The effect is economically significant. For example, in a three-year period surrounding the effective day of URAA, the bid-ask spread of treated firms decreased by 9.6%, while that of the matched control group increased by 3.9% during the same period. This is consistent with our prediction that patenting firms reduce stock illiquidity significantly more than nonpatenting firm after the implementation of TRIPS. While stock liquidity of patenting firms have a significant increasing trend after TRIPS, the trend of the control group is not as clear. The estimate for the post-TRIPS indicator is significantly negative for *Ln(Amihud)* and *-Ln(Turnover)* but significantly positive for Ln(Bid-Ask Spread).

Figures 6 to 8 demonstrate the change in stock liquidity around TRIPS for the patenting firms and control firms. All these figures show that there was no significant difference in the trend of stock liquidity between two groups until when TRIPS was in effect. Take Figure 7 for instance, after the patent law change, the bid-ask spread of patenting firms decrease dramatically while that of the control firms remain roughly at the same level in the following year. The patterns shown in the figures are consistent with estimates in the diff-in-diff model that after the implementation of TRIPS, firms that applied for patents increases stock liquidity significantly compared to firms that did not apply for patents.

A key identifying assumption for all diff-in-diff models is "parallel trends"(Roberts and Whited, 2010). It means that prior to the exogenous shock to patent rights protection, there should be no significant difference in the trend of stock liquidity between treated firms and control firms. Otherwise, the difference in trends identified by the model may be due to some preexisting factors rather than the new law that strengthens patent rights protection. Based on Figures 6 to 8, it appears that the trend of stock liquidity of the two groups start to diverge only after the implementation of TRIPS and this is consistent with the parallel trends assumption. As a robustness check, we formally test this assumption using placebo tests. We reestimate model (6) by assuming that treatment takes place in 1992 or 1993. If parallel trends assumption does not hold and stock liquidity of treated firms have been increasing more than control firms prior to the real treatment, β_2 will still be significantly negative. However, estimates reported in Table 24 in the Appendix show that β_2 is not significant in any specification of the placebo tests. This finding confirms our observation in the figures and suggests that prior to the new patent law there no significant difference in the trend of stock liquidity between treated firms and control firms. This supports our notion that the improvement in stock liquidity for patenting firms over this period is attributed to the strengthened patent rights protection.

Given more information released through patenting by patenting firms post-TRIPS, information quality about future earnings may improve in the market. To show this we use the diff-in-diff model to test the change in information quality about earnings measured by the dispersion and error of analysts' forecasts around TRIPS. Estimates are reported in Table 19. Column 1 and 2 show that analyst dispersion decrease significantly for patenting firms but not for control firms in both 3-year and 7-year window. Similar results are found for analyst forecasts error as shown in column 3 and 4. Both the decrease in analyst dispersion and forecast error reflect lower information asymmetry of patenting firms as they issue more earnings forecasts after TRIPS.

2.5.2.2 Who Are More Affected By TRIPS?

Next, we test several predicted heterogeneity of the effect of TRIPS on stock liquidity in order to rule out the possible confounding events. First, the purpose of TRIPS is protect the IP rights of firms involved in international trades. Therefore, industries more reliant on export are more likely to benefit from the new law and we expect firms in industries with larger fraction of sales from export or firms to have larger liquidity improvement after TRIPS. We test this prediction by estimating a difference-in-differences model among patenting firms, interacting *Post TRIPS* with export reliance of an industry. For each 4-digit SIC industry, we divide the total export value prior to TRIPS by the total sales of all COMPUSTAT firms in that industry in the same year.[12] Since the denominator only represents sales by public firms but not all the firms in this industry, the ratio of export to total sales may be greater than one. In that case we winsorize the ratio at one. If industries with more export benefit more from better IP rights protections, we expect the interaction term to be significantly negative. We present the estimation results in Panel A of Table 20. The interaction term is negative across all specifications and significant in three of the six specifications, supporting our prediction that industries more reliant on foreign sales benefit more from TRIPS.

Further, industries that do not have a reliable alternative to patent (e.g. trade secret) may benefit more from the strengthening of patent right. For an industry, trade secret may be a costly way to protect IP if dispute regarding trade secret takes place frequently. In that sense, industries that have experienced a lot of trade secret litigations may find patents more valuable especially when the protection is strengthened by TRIPS. We therefore estimate a difference-in-differences model among patenting firms interact *Post TRIPS* with the rank of trade secret dispute frequency of an industry. Lerner (2006) collects historical records of California and Massachusetts state cases in as well as federal cases on trade secret litigation and aggregate the number at the level of 3-digit SIC industry. We rank the industries based on the number of cases and interact it with the indicator of *Post TRIPS* in our regression.[13] The results in

[12]The industry level export data is collected from the U.S. Census.

[13]The rank of industries in descending order of number of trade secret cases is: Computer Programming (737), Miscellaneous Business Services (738), Insurance Agents, Brokers and Service (641), Electronic Components and Accessories (367), Professional and Commercial Equipment (504), Services to Dwellings and Other Buildings (734), Laundry, Cleaning and Garment Services (721), Eating And Drinking Places (581), and other. We rank these industries from 8 to 1 and the rest of industries are coded as 0. Please refer to Table 3 of Lerner (2006) for more detail.

Panel B of Table 20 show that the interaction between *Post TRIPS* and *Trade Secret Dispute Rank* is negative and significant at least 10% in four out of six specifications, indicating firms in industries with more trade secret disputes experience greater increase in stock liquidity. This is consistent with our prediction as industries with more trade secret disputes may find patents more valuable when patent protection is stronger. Both this and the results on export support that the increase in liquidity is caused by TRIPS rather than other confounding events.

The marginal benefit from an improvement in patent protection may be different across firms. Similar to the case of trade secret protection, large firms may gain relatively little from a stronger patent protection because legal protection is not necessary for them to compete against other firms. For example, even in the absence of patent protection, IBM or Microsoft can compete against copycat firms with their dominant market power. On the other hand, the marginal benefit of improved patent protection could be much greater for small firms. Given the vulnerable position of small firms in the competition, they are more likely to utilize patent rights to protect themselves from IP infringement through litigation (Lanjouw and Schankermanm, 2004). Moreover, an extension in patent term grants small firms more time to exploit their technology and this extra time could be critical to their survival in the business. Small firms are also more subject to information asymmetry problem compared to large firms. Therefore, small firms are more likely to benefit from the improvement of patent protection compared with large firms. To test this, we perform a diff-in-diff regressions among patenting firms where we interact *Post TRIPS* with an indicator of small firms. *Small Firm* is either indicated by firms with total assets or market share below the median prior to TRIPS.[14] The estimates of the model presented in Panel A of Table 21 show that the interaction term between *Post TRIPS* and *Low*

[14] Market share is defined as the fraction of sales the firm accounted for in the corresponding 4-digit SIC industry

Ln(Assets) indicator is significantly positive at 1% level in all specifications. Similar findings are shown for market share in Panel B. These results suggest that among patenting firms, firms that are small in terms of assets or market share benefit more from the strengthened patent rights protection and experience greater increase in stock liquidity.

2.5.2.3 TRIPS and Equity Financing

With an increase in stock liquidity after strengthened patent rights, firms should benefit by gaining easier access to equity financing. This is especially important for small firms or financially constrained firms that may lack other sources of financing. In this section we ask whether firms do take advantage of increased liquidity after TRIPS by raising equity capital. To test this we again estimate a Diff-in-Diff model. This time we use firm's SEO activities as the dependent variable. We estimate the following firm fixed effects logit model:

$$\Pr(\text{SEO})_{i,t} = \alpha_4 + \beta_7 \text{Post}_{i,t} + \beta_8 \text{Post}_{i,t} \times \text{Treated}_i + \gamma_4' CONTROL_{i,t-1} + \phi_i + \epsilon_{i,t}. \quad (9)$$

SEO is a binary variable that equal one if the firm issue an SEO in that year and zero otherwise. Panel A of Table 22 shows the results. In columns 1 and 2 we estimate the model in the full sample and estimate the different between patenting firms and non-patenting firms. The estimates show that patenting firms on average are not significantly more likely to raise equity capital following TRIPS. In columns 3 to 6, we estimate the model among patenting firms and test the difference between large firms and small firms or between constrained firms and unconstrained firms. The estimates show that firms with smaller size, without paying dividends or access to public debt, are significantly more likely to issue SEO after TRIPS.

In Panel B, we compare the market reaction to SEOs before and after TRIPS. We do pooled OLS model regressing SEO CARs over different horizon on *Post TRIPS* indicator with a set of firm controls. The estimates show that market reaction to SEOs is significantly better after TRIPS. This result is robust to CAR over various horizons. SEOs after TRIPS are associated with 9.7% higher abnormal return over one year post SEOs. This higher frequency of SEOs among small and financially constrained firms after TRIPS and the better market performance suggest that TRIPS plays a role in reducing financing friction by improving stock liquidity.

2.6 Conclusion

In this paper, we find that different forms of IP protection have distinct implications to firms' equity financing. Stronger secrecy protection encourages firms to adopt more secrecy, therefore increases information asymmetry and reduces stock liquidity. By contrast, better patent protection causes firms to disclose more information by patenting their inventions, resulting in higher stock liquidity. We find these results by exploiting exogenous law changes, such as state trade secret statute and the implementation of TRIPS, that improves the protection of either form of IP. Consistent with the notion that higher stock liquidity is associated with lower cost in raising equity capital, we find that SEOs after TRIPS (trade secret statute) are associated with higher (lower) abnormal return in various horizons.

Our findings provide policy makers and academic researchers with a new perspective for the discussion and future development of IP protection law. In particular, our findings show that IP protection plays a more important role in the financing of small firms, who typically are in a more vulnerable position in product market and encounter more frictions in raising capital. Therefore, our study has important implication to policies that aim to facilitate growth of small innovative firms.

Table 11: Trade Secrets Law in the US.

Column 1 presents the year in which states enacted a trade secrets statute. Column 2 shows an index compiled by Png (2014) measuring the strength of trade secrets protection under common law. Column 3 shows the increase in the protection after the enactment of statute. The index characterizes three aspects of the law of trade secrets: substantive law, procedure, and remedies. Details of the index can be found in Png (2014)

State	Year	Common Law	Statute
Alaska	1988	0	0.467
Arizona	1990	0.25	0.217
Arkansas	1981	0.5	0
California	1985	0.22	0.247
Colorado	1986	0	0.767
Connecticut	1983	0	0.467
Delaware	1982	0	0.467
District of Columbia	1989	0	0.467
Florida	1988	0.1	0.367
Georgia	1990	0	0.7
Hawaii	1989	0	0.467
Idaho	1981	0	0.467
Illinois	1988	0	0.7
Indiana	1982	0	0.467
Iowa	1990	0	0.467
Kansas	1981	0	0.467
Kentucky	1990	0	0.467
Louisiana	1981	0	0.4
Maine	1987	0	0.5
Maryland	1989	0.22	0.247
Michigan	1998	0.25	0
Minnesota	1980	0	0.467
Mississippi	1990	0	0.567
Missouri	1995	0	0.633
Montana	1985	0	0.567
Nebraska	1988	0	0
Nevada	1987	0	0.467
New Hampshire	1990	0.025	0.442
New Mexico	1989	0	0.467
North Dakota	1983	0	0.467
Ohio	1994	0.25	0.283
Oklahoma	1986	0.025	0.442
Oregon	1988	0	0.467
Rhode Island	1986	0	0.467
South Dakota	1988	0	0.467
Utah	1989	0	0.467
Vermont	1996	0	0.567
Virginia	1986	0.025	0.442
Washington	1982	0	0.467
West Virginia	1986	0	0.467

Table 12: Summary Statistics For Chapter 2.

Panel A presents summary statistics of the main variables used in our analyses of trade secret statute. Panel B compares the summary statistics of the treated group and control group used in the analyses of TRIPS. We use propensity score matching for which the estimation is presented in the Appendix. We winsorize all firm and loan characteristics at the 1st and 99th percentiles. All the variables are defined in the Appendix.

Panel A

	N	**Mean**	**Median**	**S.D.**
Ln(Amihud)	45,844	5.399	5.511	2.967
-Ln(Share Turnover)	45,861	5.944	5.937	1.021
Ln(Assets)	46,147	4.750	4.517	1.948
Leverage	46,147	0.240	0.213	0.206
Q	46,147	1.913	1.325	1.657
Profitability	46,147	-0.006	0.042	0.265
Cash	46,147	0.152	0.066	0.196
Tangibility	46,147	0.318	0.260	0.239
Ln(Age)	46,147	2.171	2.272	1.001
Return Volatility	46,147	0.036	0.032	0.021
Ln(Number of Analysts)	46,147	1.217	1.099	1.068
Market Share	46,147	0.030	0.015	12.957
Ln(Analyst Dispersion)	27,188	2.218	1.993	1.160
Ln(Analyst Error)	31,794	3.135	2.960	1.508
Ln(Patent Applications)	46,147	0.495	0.000	1.049
SEO Dummy	46,147	0.063	0.000	0.243

Panel B

	Control Group				*Treated Group*			
	N	**Mean**	**Median**	**S.D.**	**N**	**Mean**	**Median**	**S.D.**
Ln(Amihud)	4,744	4.941	4.800	2.847	6,341	4.418	4.218	2.707
Ln(Bid-Ask Spread)	4,679	-3.529	-3.546	0.851	6,227	-3.665	-3.673	0.813
-Ln(Turnover)	4,744	5.884	5.900	0.998	6,341	5.729	5.714	0.966
Ln(Assets)	4,744	5.227	5.006	2.029	6,343	5.265	5.013	1.990
Leverage	4,744	0.205	0.162	0.201	6,343	0.194	0.162	0.182
Q	4,744	1.924	1.340	1.774	6,343	2.118	1.583	1.644
Profitability	4,744	0.009	0.040	0.263	6,343	-0.016	0.048	0.304
Cash	4,744	0.154	0.066	0.196	6,343	0.178	0.080	0.221
Tangibility	4,744	0.280	0.195	0.249	6,343	0.274	0.244	0.172
Ln(Age)	4,744	2.208	2.342	1.169	6,343	2.297	2.500	1.237
Return Volatility	4,744	0.035	0.030	0.022	6,343	0.034	0.030	0.019
Ln(Number of Analysts)	4,744	1.402	1.386	1.050	6,343	1.472	1.609	1.017

Table 13: Trade Secret Law and Stock Liquidity of Small Firms

In this table, we show that the impact of trade secret statute on stock liquidity is concentrated among small firms. The dependent variables are measures of stock illiquidity including *Ln(Amihud)* and *-Ln(Turnover)* and the independent variables of interest are *TS Law* and its interaction with indicators of small firms. The following lagged firm characteristics are also included in the regressions: *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Cash*, *Tangibility*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*. Firm and year fixed effects are also included. *t*-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variables	*Ln(Amihud)*			*-Ln(Turnover)*		
	(1)	(2)	(3)	(4)	(5)	(6)
TS Law	0.109	-0.431***	-0.125	0.109***	0.032	0.085*
	(1.52)	(-4.79)	(-1.56)	(2.76)	(0.74)	(1.86)
TS Law × Low Ln(Assets)		1.442***			0.202***	
		(11.24)			(3.07)	
TS Law × Low Market Share			0.637***			0.065
			(5.67)			(1.05)
Low Ln(Assets)		0.061			-0.021	
		(0.88)			(-0.62)	
Low Market Share			-0.291***			-0.018
			(-4.75)			(-0.54)
Ln(Assets)	-0.892***		-0.889***	-0.089***		-0.087***
	(-36.70)		(-35.66)	(-6.60)		(-6.36)
Leverage	1.168***	0.653***	1.176***	0.055	0.004	0.056
	(14.74)	(7.86)	(14.82)	(1.22)	(0.09)	(1.25)
Q	-0.443***	-0.388***	-0.442***	-0.086***	-0.080***	-0.086***
	(-42.63)	(-36.77)	(-42.39)	(-19.41)	(-18.43)	(-19.36)
Profitability	-0.743***	-0.874***	-0.746***	-0.241***	-0.254***	-0.241***
	(-14.04)	(-15.38)	(-14.09)	(-9.57)	(-10.06)	(-9.56)
Cash	-0.337***	-0.326***	-0.338***	-0.076	-0.076	-0.078
	(-3.79)	(-3.39)	(-3.82)	(-1.57)	(-1.57)	(-1.60)
Tangibility	0.237**	0.433***	0.236**	0.142**	0.160**	0.141**
	(1.97)	(3.20)	(1.97)	(2.25)	(2.53)	(2.25)
Ln(Age)	0.168***	0.034	0.155***	0.058***	0.042**	0.056***
	(5.22)	(0.91)	(4.83)	(3.30)	(2.36)	(3.20)
Return Volatility	17.771***	22.003***	17.633***	-2.377***	-1.974***	-2.392***
	(23.70)	(29.36)	(23.55)	(-5.43)	(-4.60)	(-5.47)
Ln(Number of Analysts)	-0.311***	-0.595***	-0.312***	-0.127***	-0.156***	-0.127***
	(-15.61)	(-28.42)	(-15.68)	(-11.54)	(-15.25)	(-11.54)
Adjusted R^2	0.896	0.885	0.896	0.746	0.745	0.746
Observations	45,844	45,844	45,844	45,861	45,861	45,861
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 14: Trade Secret Law and Analyst Forecast

In this table, we show that stock opacity in terms of analyst forecast dispersion and forecast error increases after the enactment of trade secret statute. The dependent variables are *Ln(Analyst Dispersion)* and *Ln(Analyst Error)* and the independent variables of interest are *TS Law* and its interaction with indicators of small firms. The following lagged firm characteristics are also included in the regressions: *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Cash*, *Tangibility*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*. Firm and year fixed effects are also included. *t*-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variables	*Ln(Analyst Dispersion)*			*Ln(Analyst Error)*		
	(1)	(2)	(3)	(4)	(5)	(6)
TS Law	0.176**	0.192***	0.120	0.222**	0.274***	0.160*
	(2.53)	(2.64)	(1.59)	(2.53)	(2.96)	(1.66)
TS Law × Low Ln(Assets)		-0.096			-0.234	
		(-0.70)			(-1.48)	
TS Law × Low Market Share			0.236*			0.234
			(1.85)			(1.57)
Low Ln(Assets)		-0.011			-0.016	
		(-0.16)			(-0.21)	
Low Market Share			-0.054			-0.078
			(-0.80)			(-0.99)
Ln(Assets)	0.094***		0.098***	0.104***		0.107***
	(3.84)		(4.01)	(3.51)		(3.56)
Leverage	0.690***	0.743***	0.694***	0.671***	0.717***	0.675***
	(7.28)	(8.00)	(7.33)	(6.45)	(6.99)	(6.49)
Q	-0.084***	-0.087***	-0.083***	-0.071***	-0.075***	-0.070***
	(-9.29)	(-9.71)	(-9.24)	(-7.02)	(-7.60)	(-6.97)
Profitability	-0.874***	-0.871***	-0.873***	-0.332***	-0.326***	-0.331***
	(-11.82)	(-11.85)	(-11.80)	(-5.96)	(-5.90)	(-5.94)
Cash	-0.125	-0.126	-0.128	-0.412***	-0.410***	-0.414***
	(-1.20)	(-1.21)	(-1.23)	(-3.52)	(-3.52)	(-3.54)
Tangibility	0.701***	0.647***	0.701***	0.347**	0.300*	0.347**
	(4.71)	(4.36)	(4.73)	(2.04)	(1.79)	(2.05)
Ln(Age)	0.095***	0.112***	0.093***	0.026	0.037	0.023
	(3.02)	(3.56)	(2.94)	(0.68)	(0.95)	(0.60)
Return Volatility	10.237***	9.794***	10.189***	1.511	1.119	1.461
	(8.86)	(8.54)	(8.83)	(1.43)	(1.07)	(1.39)
Ln(Number of Analysts)	0.207***	0.237***	0.208***	0.144***	0.173***	0.144***
	(10.69)	(12.96)	(10.71)	(6.30)	(8.07)	(6.29)
Adjusted R^2	0.531	0.531	0.532	0.370	0.370	0.370
Observations	27,188	27,188	27,188	31,794	31,794	31,794
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 15: Trade Secret Law and Patenting Activities

In this table, we show that small firms tend to reduce patenting after the enactment of trade secret statute. The dependent variable is *Ln(Patent Applications)* and the independent variables of interest are the interaction between *TS Law* and the binary variable indicating firms *Ln(Assets)* or *Market Share* below the sample median. The following lagged firm characteristics are also included in the regressions: *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Cash*, *Tangibility*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*. Firm and year fixed effects are also included. *t*-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

	Dependent Variable: *Ln(Patent Applications)*		
	(1)	(2)	(3)
TS Law	-0.069*	-0.029	-0.034
	(-1.90)	(-0.60)	(-0.74)
TS Law × Low Ln(Assets)		-0.113**	
		(-2.36)	
TS Law × Low Market Share			-0.098**
			(-2.14)
Low Ln(Assets)		-0.043	
		(-1.55)	
Low Market Share			0.065**
			(2.49)
Ln(Assets)	0.162***		0.164***
	(9.36)		(9.39)
Leverage	-0.145***	-0.043	-0.146***
	(-4.10)	(-1.36)	(-4.13)
Q	0.027***	0.017***	0.027***
	(5.71)	(3.61)	(5.67)
Profitability	-0.029	-0.005	-0.028
	(-1.40)	(-0.27)	(-1.35)
Cash	0.025	0.020	0.023
	(0.63)	(0.50)	(0.57)
Tangibility	0.082*	0.043	0.082*
	(1.80)	(0.95)	(1.80)
Ln(Age)	0.051***	0.074***	0.053***
	(3.06)	(4.02)	(3.18)
Return Volatility	-0.216	-1.102***	-0.196
	(-0.93)	(-4.97)	(-0.85)
Ln(Number of Analysts)	-0.006	0.049***	-0.006
	(-0.65)	(5.24)	(-0.62)
Adjusted R^2	0.845	0.841	0.845
Observations	46,147	46,147	46,147
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Table 16: Trade Secret Law and Seasoned Equity Offerings

In this table, we show that small firms are more likely to issue SEO after the enactment of trade secret statute. We estimate a conditional logit model where the dependent variable is *Ln(Patent Applications)* and the independent variables of interest are the interaction between *TS Law* and the binary variable indicating firms *Ln(Assets)* or *Market Share* below the sample median. The following lagged firm characteristics are also included in the regressions: *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Cash*, *Tangibility*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*. Firm and year fixed effects are also included. *t*-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

	Dependent Variable: *SEO Dummy*		
	(1)	(2)	(3)
TS Law	0.085	-0.226	-0.128
	(0.40)	(-0.96)	(-0.53)
TS Law × Low Ln(Assets)		1.042***	
		(3.19)	
TS Law × Low Market Share			0.653*
			(1.93)
Low Ln(Assets)		0.072	
		(0.45)	
Low Market Share			-0.081
			(-0.46)
Ln(Assets)	-0.452***		-0.430***
	(-7.23)		(-6.80)
Leverage	2.240***	2.035***	2.251***
	(9.00)	(8.58)	(9.07)
Q	0.315***	0.346***	0.316***
	(13.10)	(14.82)	(13.16)
Profitability	0.527***	0.425***	0.526***
	(3.55)	(3.05)	(3.54)
Cash	-1.447***	-1.484***	-1.473***
	(-4.94)	(-5.18)	(-5.01)
Tangibility	-0.492	-0.363	-0.507
	(-1.32)	(-1.02)	(-1.37)
Ln(Age)	-0.110	-0.197**	-0.122
	(-1.32)	(-2.47)	(-1.46)
Return Volatility	-11.259***	-9.813***	-11.442***
	(-4.35)	(-3.88)	(-4.42)
Ln(Number of Analysts)	-0.203***	-0.316***	-0.203***
	(-3.73)	(-6.30)	(-3.72)
Adjusted R^2	0.148	0.145	0.148
Observations	17,661	17,661	17,661
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Table 17: Trade Secret Law and Market Reaction to SEOs

In this table, we show that the stock market reacts more positively to SEOs after trade secret statute. The dependent variables are cumulative abnormal return over different horizons around SEOs and the independent variables of interest is *TS Law* . The following lagged firm characteristics are also included in the regressions: *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Cash*, *Tangibility*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*. State and year fixed effects are also included. *t*-statistics using robust standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variables	*CAR(-1,+1)* (1)	*CAR(-1,+10)* (2)	*CAR(0,+60)* (3)	*CAR(0,+250)* (4)
TS Law	0.002	-0.039**	-0.056*	-0.171**
	(0.24)	(-2.42)	(-1.65)	(-2.37)
Ln(Assets)	0.001	-0.001	-0.005	-0.004
	(0.58)	(-0.31)	(-1.14)	(-0.44)
Leverage	0.002	0.008	-0.004	-0.136**
	(0.20)	(0.63)	(-0.13)	(-2.00)
Q	-0.002	-0.004*	-0.004	-0.009
	(-1.57)	(-1.73)	(-0.87)	(-0.89)
Profitability	0.011*	0.014	0.064***	0.119**
	(1.91)	(1.57)	(3.11)	(2.24)
cash	0.016	0.026	-0.004	-0.010
	(1.61)	(1.52)	(-0.13)	(-0.13)
Tangibility	0.012**	0.003	-0.023	0.038
	(2.19)	(0.32)	(-1.03)	(0.84)
Ln(Age)	0.002	0.003	-0.002	-0.006
	(1.09)	(1.06)	(-0.30)	(-0.47)
Return Volatility	-0.060	0.329	-0.054	0.342
	(-0.42)	(1.29)	(-0.10)	(0.31)
Ln(Number of Analyst)	-0.004**	-0.004	0.010	0.013
	(-2.51)	(-1.25)	(1.40)	(0.88)
Adjusted R^2	0.012	0.018	0.029	0.038
Observations	2,424	2,424	2,426	2,426
State Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table 18: Change in Stock Liquidity Around TRIPS.

In this table, we present Diff-in-Diffs estimates where the dependent variable are measures of stock illiquidity including *Ln(Amihud)*, *Ln(Bid-Ask Spread)* and *-Ln(Turnover)* and the independent variables of interest is the interaction term between *Post TRIPS* and *Treated*. The following lagged firm characteristics are also included in the regressions: *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Cash*, *Tangibility*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*. Firm fixed effects are also included. Column 1, 3, 5 present estimates in the 3-year window while column 2, 4, 6 present estimates in the 7-year window around the law change. *t*-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

	Ln(Amihud)		*Ln(Bid-Ask Spread)*		*-Ln(Turnover)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Post TRIPS	-0.223***	-0.264***	0.008	0.043**	-0.118***	-0.166***
	(-4.94)	(-6.62)	(0.38)	(2.16)	(-4.19)	(-6.73)
Post TRIPS × Treated	-0.174***	-0.185***	-0.059**	-0.088***	-0.072**	-0.052*
	(-3.04)	(-3.70)	(-2.33)	(-3.51)	(-2.12)	(-1.75)
Ln(Assets)	-0.796***	-0.841***	-0.163***	-0.261***	-0.051	-0.083***
	(-9.96)	(-19.53)	(-5.37)	(-14.31)	(-1.06)	(-3.46)
Leverage	0.512	0.916***	0.166	0.323***	-0.259	-0.105
	(1.62)	(6.00)	(1.42)	(4.49)	(-1.52)	(-1.21)
Q	-0.337***	-0.353***	-0.080***	-0.087***	-0.072***	-0.086***
	(-11.06)	(-20.14)	(-8.38)	(-14.28)	(-6.41)	(-11.91)
Profitability	-0.327**	-0.454***	-0.072	-0.125***	-0.123**	-0.172***
	(-2.44)	(-5.62)	(-1.56)	(-4.38)	(-2.26)	(-4.31)
Cash	-0.030	-0.302*	-0.002	-0.048	0.222	0.005
	(-0.11)	(-1.84)	(-0.02)	(-0.71)	(1.43)	(0.05)
Tangibility	1.026**	0.665***	0.200	-0.029	0.386	0.333**
	(2.36)	(2.80)	(1.36)	(-0.28)	(1.59)	(2.51)
Ln(Age)	-0.274***	-0.078**	-0.114***	-0.104***	-0.078**	0.056***
	(-3.98)	(-2.32)	(-4.77)	(-6.55)	(-2.13)	(2.84)
Return Volatility	1.095	12.415***	0.235	4.827***	-0.566	-2.417***
	(0.42)	(8.09)	(0.26)	(8.15)	(-0.38)	(-2.83)
Ln(Number of Analysts)	0.011	-0.192***	0.033	0.014	0.033	-0.077***
	(0.17)	(-5.72)	(1.29)	(0.84)	(0.90)	(-3.98)
Adjusted R^2	0.934	0.920	0.865	0.813	0.836	0.789
Observations	5,241	11,085	5,236	10,906	5,241	11,085
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Years	3	7	3	7	3	7

Table 19: Change in the Analyst Forecast Dispersion and Error Around TRIPS.

In this table, we present estimates from Diff-in-Diffs models where the dependent variable are *Ln(Analyst Dispersion)* and *Ln(Analyst Error)* and the independent variables of interest is the interaction term between *Post TRIPS* and *Treated*. The following lagged firm characteristics are also included in the regressions: *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Cash*, *Tangibility*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*. Firm fixed effects are also included. Column 1, and 3 present estimates in the 3-year window while column 2, and 4 present estimates in the 7-year window around the change of patent law. *t*-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

	Ln(Analyst Dispersion)		Ln(Analyst Error)	
	(1)	(2)	(3)	(4)
Post TRIPS	0.053	-0.011	0.152*	0.075
	(0.94)	(-0.24)	(1.79)	(1.32)
Post TRIPS × Treated	-0.223***	-0.219***	-0.096	-0.217***
	(-3.29)	(-4.08)	(-0.93)	(-3.09)
Ln(Assets)	0.260**	0.065	0.270*	0.136**
	(2.37)	(1.34)	(1.84)	(2.26)
Leverage	0.010	0.315*	-0.102	0.251
	(0.02)	(1.73)	(-0.25)	(1.13)
Q	-0.052**	-0.077***	0.011	-0.009
	(-2.07)	(-4.78)	(0.41)	(-0.53)
Profitability	-0.334*	-0.451***	0.166	-0.054
	(-1.87)	(-4.41)	(1.04)	(-0.66)
Cash	-0.775**	-0.559***	-0.322	-0.774***
	(-2.13)	(-2.68)	(-0.77)	(-3.37)
Tangibility	0.815	0.718**	1.311*	0.578*
	(1.39)	(2.48)	(1.77)	(1.76)
Ln(Age)	0.039	0.036	-0.127	-0.039
	(0.42)	(0.96)	(-1.17)	(-0.84)
Return Volatility	1.327	7.634***	-8.192*	0.273
	(0.31)	(3.08)	(-1.90)	(0.13)
Ln(Number of Analysts)	0.152	0.252***	0.264**	0.302***
	(1.62)	(5.93)	(2.13)	(5.59)
Adjusted R^2	0.595	0.559	0.456	0.421
Observations	3,559	7,537	4,084	8,606
Firm Fixed Effects	Yes	Yes	Yes	Yes
Number of Years	3	7	3	7

Table 20: Foreign Sales, Trade Secret Disputes, and Change in Stock Liquidity Around TRIPS.

In this table, we present estimates from Diff-in-Diffs models among treated firms where the dependent variable are measures of stock illiquidity including *Ln(Amihud)*, *Ln(Bid-Ask Spread)* and *-Ln(Turnover)* and the independent variables of interest is the interaction term between *Post* and *Export* (Panel A) or *Trade Secret Disputes Rank* (Panel B). The following lagged firm characteristics are also included in the regressions: *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Cash*, *Tangibility*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*. Firm fixed effects are also included. Column 1, 3, 5 present estimates in the 3-year window while column 2, 4, 6 present estimates in the 7-year window around the implementation of TRIPS. t-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Panel A: Foreign Sales

	Ln(Amihud)		*Ln(Bid-Ask Spread)*		*-Ln(Turnover)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.356***	-0.336***	-0.069**	-0.039	-0.181***	-0.173***
	(-4.87)	(-5.40)	(-2.30)	(-1.31)	(-4.58)	(-5.33)
Post × Export_{pre}	-0.245	-0.432***	-0.040	-0.088	-0.233**	-0.159*
	(-1.38)	(-2.98)	(-0.56)	(-1.25)	(-2.15)	(-1.84)
Adjusted R^2	0.923	0.908	0.868	0.818	0.848	0.797
Observations	2,143	4,749	2,141	4,678	2,143	4,749
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Years	3	7	3	7	3	7

Panel B: Trade Secret Dispute

	Ln(Amihud)		*Ln(Bid-Ask Spread)*		*-Ln(Turnover)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Post TRIPS	-0.370***	-0.417***	-0.053***	-0.030*	-0.195***	-0.207***
	(-9.57)	(-12.27)	(-3.07)	(-1.75)	(-8.87)	(-11.61)
Post TRIPS	-0.023	-0.024	-0.026***	-0.029***	-0.019*	-0.020**
× Trade Secret Dispute Rank	(-1.14)	(-1.32)	(-3.62)	(-3.89)	(-1.87)	(-2.32)
Adjusted R^2	0.935	0.921	0.877	0.823	0.854	0.811
Observations	3,547	7,877	3,542	7,740	3,547	7,877
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Years	3	7	3	7	3	7

Table 21: Firm Size and Change in Stock Liquidity Around TRIPS.

In this table, we show that small firms and financially constrained firms experienced greater increase in stock liquidity after TRIPS. We present estimates from Diff-in-Diffs models among treated firms where the dependent variable are measures of stock illiquidity including *Ln(Amihud)*, *Ln(Bid-Ask Spread)* and *-Ln(Turnover)*. In Panel A and B, and the independent variables of interest is the interaction term between *Post TRIPS* and empirical proxies for small firms including *Low Ln(Assets)* and *Low Market Share*, both measured in 1994. The following lagged firm characteristics are also included in the regressions: *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Cash*, *Tangibility*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*. Firm fixed effects are also included. Column 1, 3, 5 present estimates in the 3-year window while column 2, 4, 6 present estimates in the 7-year window around the implementation of TRIPS. *t*-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Panel A: Firm Size Measured by Ln(Assets)

	Ln(Amihud)		*Ln(Bid-Ask Spread)*		*-Ln(Turnover)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Post TRIPS	-0.178***	-0.227***	-0.017	0.024	-0.128***	-0.176***
	(-5.12)	(-6.75)	(-0.86)	(1.19)	(-5.93)	(-9.56)
Post TRIPS × Low Ln(Assets)$_{pre}$	-0.458***	-0.462***	-0.110***	-0.155***	-0.173***	-0.095***
	(-6.36)	(-7.35)	(-3.40)	(-4.96)	(-4.26)	(-2.81)
Adjusted R^2	0.937	0.923	0.877	0.825	0.856	0.812
Observations	3,547	7,793	3,542	7,656	3,547	7,793
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Years	3	7	3	7	3	7

Panel B: Market Share at 4-digit SIC Level

	Ln(Amihud)		*Ln(Bid-Ask Spread)*		*-Ln(Turnover)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Post TRIPS	-0.223***	-0.289***	-0.012	0.033	-0.154***	-0.184***
	(-5.56)	(-7.62)	(-0.55)	(1.57)	(-6.21)	(-9.23)
Post TRIPS × Low Market Share$_{pre}$	-0.351***	-0.317***	-0.120***	-0.175***	-0.113***	-0.074**
	(-4.83)	(-4.95)	(-3.73)	(-5.57)	(-2.82)	(-2.18)
Adjusted R^2	0.936	0.922	0.878	0.825	0.855	0.811
Observations	3,532	7,758	3,527	7,621	3,532	7,758
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Years	3	7	3	7	3	7

Table 22: SEO Activity and Market Reaction Around TRIPS.

In Panel A, we present estimates from Diff-in-Diffs models from logit model with firm fixed effects where the dependent variable a binary variable that equal one if the firm has an SEO in that year. In Columns 1 and 2 we estimate the regression in the matched sample and the variable of interest and the independent variable of interest is the interaction term between *Post TRIPS* and *Treated*. In Columns 3 to 10 we present estimates among the treated group and the variables of interests are the interaction term between *Post TRIPS* and *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Cash*, *Tangibility*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*. Firm fixed effects are also included. Column 1, 3, 5 present estimates in the 3-year window while column 2, 4, 6 present estimates in the 7-year window around the implementation of TRIPS. t-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Panel A: Likelihood of SEO Around TRIPS

	Dependent Variable: SEO									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post TRIPS	0.793***	-0.005	0.584*	-0.118	0.917**	0.109	1.322***	0.550**	1.187***	0.500**
	(2.75)	(-0.03)	(1.65)	(-0.55)	(2.49)	(0.51)	(4.10)	(2.48)	(4.05)	(2.40)
Post TRIPS × Treated	0.149	0.151								
	(0.43)	(0.75)								
Post TRIPS × Low Ln(Assets)$_{pre}$			0.875**	0.735***						
			(2.07)	(2.72)						
Post TRIPS × Low Market Share$_{pre}$					0.193	0.273				
					(0.45)	(1.01)				
Post TRIPS × Dividend Dummy$_{pre}$							-1.005**	-0.736**		
							(-2.12)	(-2.47)		
Post TRIPS × Public Debt Dummy$_{pre}$									-0.873	-0.861***
									(-1.47)	(-2.71)
Pseudo R^2	0.241	0.130	0.299	0.146	0.290	0.139	0.300	0.144	0.295	0.146
Observations	796	2934	531	1936	528	1922	531	1890	531	1944
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Years	3	7	3	7	3	7	3	7	3	7
Sample	Full	Full	Treated	Treated	Treated	Treated	Treated	Treated	Treated	Treated

In Panel B, we show that the stock market reacts more positively to SEOs after TRIPS. The sample consists of SEOs in the seven-year period around TRIPS. The dependent variables are cumulative abnormal return over different horizons around SEOs and the independent variables of interest is *Post TRIPS*. The following lagged firm characteristics are also included in the regressions: *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Cash*, *Tangibility*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*. State and year fixed effects are also included. *t*-statistics using robust standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Panel B: Market Reaction to SEOs

Dependent Variables	*CAR(-1,+1)* (1)	*CAR(-1,+10)* (2)	*CAR(0,+60)* (3)	*CAR(0,+250)* (4)
Post TRIPS	0.006**	0.011**	0.045***	0.097***
	(2.34)	(2.30)	(4.53)	(4.59)
Ln(Assets)	0.000	0.000	0.010**	0.016
	(0.34)	(0.03)	(2.18)	(1.63)
Leverage	0.010	0.006	-0.009	-0.094
	(1.23)	(0.42)	(-0.30)	(-1.55)
Q	0.000	-0.001	0.005	0.003
	(0.13)	(-0.42)	(1.22)	(0.40)
Profitability	0.003	0.009	0.062***	0.070
	(0.54)	(1.01)	(3.30)	(1.52)
cash	0.001	-0.010	-0.010	-0.048
	(0.13)	(-0.63)	(-0.33)	(-0.65)
Tangibility	0.010*	-0.016	-0.009	0.032
	(1.66)	(-1.60)	(-0.43)	(0.74)
Ln(Age)	0.002	0.002	-0.007	-0.013
	(1.14)	(0.66)	(-1.43)	(-1.15)
Return Volatility	-0.110	0.569**	0.479	0.897
	(-0.68)	(2.05)	(1.02)	(0.90)
Ln(Number of Analysts)	-0.003	0.003	0.000	-0.003
	(-1.58)	(0.80)	(0.07)	(-0.20)
Adjusted R^2	0.005	0.005	0.019	0.011
Observations	2,055	2,055	2,057	2,057
Number of Years	7	7	7	7

Table 23: Propensity Score Matching Regressions and Summary Statistics.

This table presents probit regressions used for propensity score matching in the year prior to TRIPS. The dependent variable equals to 1 if the firm has applied for patents in 1993 or 1994 (treatment group) and 0 otherwise (control group). Column 1 presents estimates in the entire sample in the year before TRIPS including 1,178 treatment firms and 3,293 control firms. Column 2 presents estimates in the matched sample, where 1,033 treatment firms are matched to 786 control firms.

	Pre-Match (1)	*Post-Match* (2)
Ln(Assets)	0.059***	-0.011
	(2.76)	(-0.36)
Leverage	-0.413***	0.087
	(-3.28)	(0.46)
Q	0.101***	0.029
	(6.21)	(1.04)
Profitability	-0.200***	-0.023
	(-2.85)	(-0.23)
Cash	0.917***	0.414**
	(7.06)	(2.22)
Tangibility	-0.560***	0.178
	(-5.95)	(1.05)
Ln(Age)	0.164***	0.031
	(8.47)	(1.13)
Return Volatility	-2.271*	-3.423*
	(-1.73)	(-1.72)
Ln(Number of Analysts)	0.169***	0.001
	(4.99)	(0.02)
Pseudo R^2	0.098	0.005
Observations	4,471	1,819

Table 24: Placebo Test: Diff-in-Diff Regressions around 1992 and 1993

This table presents estimates from the Diff-in-Diff regressions using annual data in the 3-year window around 1992 or 1993 to test the parallel trends in stock liquidity prior to the implementation of TRIPS. In column 1 to 3 (4 to 6), we use 1993 (1992) as the event year and match treatment firms with control firms in the preceding year. *Post* equals to 1 if the observation is in or after year 1993 (1992). The following lagged firm characteristics are also included in the regressions: *Ln(Assets)*, *Leverage*, *Q*, *Profitability*, *Cash*, *Tangibility*, *Ln(Age)*, *Return Volatility*, and *Ln(Number of Analysts)*. Firm fixed effects are also included. t-statistics using robust, firm-clustered standard errors are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

	1992-1994			1991-1993		
	Ln(Amihud)	*Ln(Spread)*	*-Ln(Turnover)*	*Ln(Amihud)*	*Ln(Spread)*	*-Ln(Turnover)*
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.185***	-0.010	-0.075***	-0.131*	-0.010	-0.044
	(-3.81)	(-0.49)	(-2.76)	(-1.85)	(-0.30)	(-1.37)
Post × Innovative	-0.035	-0.029	0.049	-0.108	-0.011	-0.019
	(-0.57)	(-1.13)	(1.41)	(-1.40)	(-0.28)	(-0.49)
Ln(Assets)	-0.567***	-0.114***	0.009	-0.514***	0.005	0.099
	(-5.86)	(-3.54)	(0.21)	(-4.69)	(0.10)	(1.64)
Leverage	0.966***	0.268*	-0.084	0.767**	0.197	-0.152
	(2.59)	(1.76)	(-0.42)	(2.12)	(1.06)	(-0.82)
Q	-0.244***	-0.047***	-0.054***	-0.263***	-0.056***	-0.058***
	(-6.74)	(-4.97)	(-3.92)	(-7.01)	(-4.55)	(-3.75)
Profitability	-0.166*	-0.058*	-0.049	-0.435	-0.138	-0.088
	(-1.65)	(-1.76)	(-0.97)	(-1.40)	(-1.00)	(-0.90)
Cash	-0.354	-0.249	0.012	-0.707*	-0.213	-0.106
	(-1.26)	(-1.64)	(0.08)	(-1.75)	(-1.41)	(-0.54)
Tangibility	0.378	0.055	0.242	1.132*	0.241	0.275
	(0.70)	(0.29)	(0.97)	(1.89)	(0.98)	(0.87)
Ln(Age)	0.070	0.018	0.083**	-0.122	-0.092**	0.025
	(0.85)	(0.55)	(2.53)	(-1.23)	(-2.53)	(0.58)
Return Volatility	4.325*	-0.082	-2.367	5.741**	-0.688	-2.182
	(1.69)	(-0.08)	(-1.60)	(2.10)	(-0.70)	(-1.51)
Ln(Number of Analysts)	0.027	0.024	0.023	0.113	0.080**	0.043
	(0.37)	(0.86)	(0.61)	(1.33)	(2.15)	(1.05)
Adjusted R^2	0.945	0.916	0.852	0.934	0.918	0.833
Observations	4,378	4,205	4,378	3,979	3,096	3,979
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

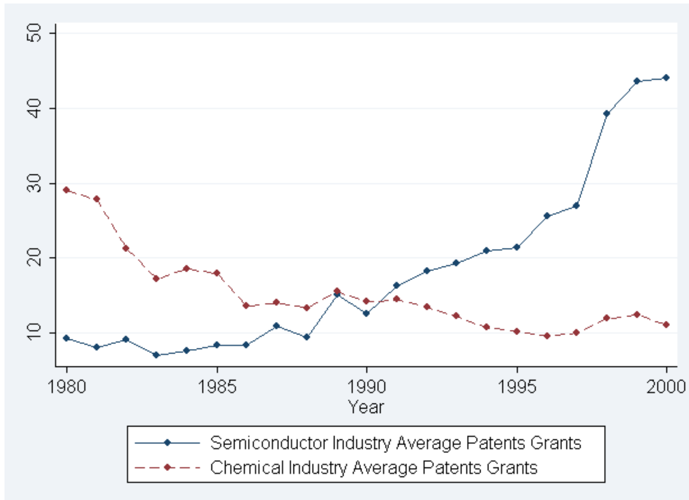


Figure 3: Average Patent Grants for Firms in the Semiconductor and Chemical Industry 1980-2005

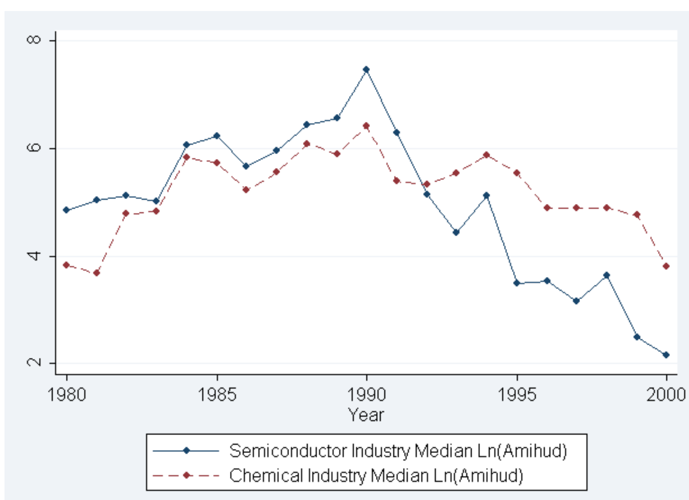


Figure 4: Average Ln(Amihud) for Firms in the Semiconductor and Chemical Industry 1980-2005

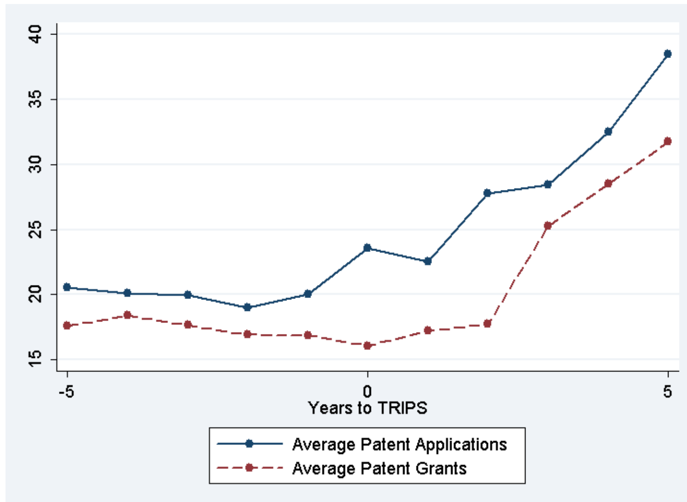


Figure 5: Patent Applications and Patent Grants Around TRIPS

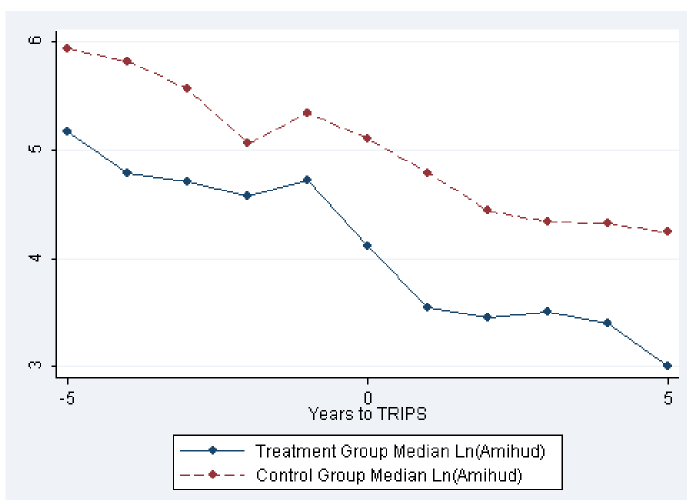


Figure 6: Ln(Amihud) Around TRIPS

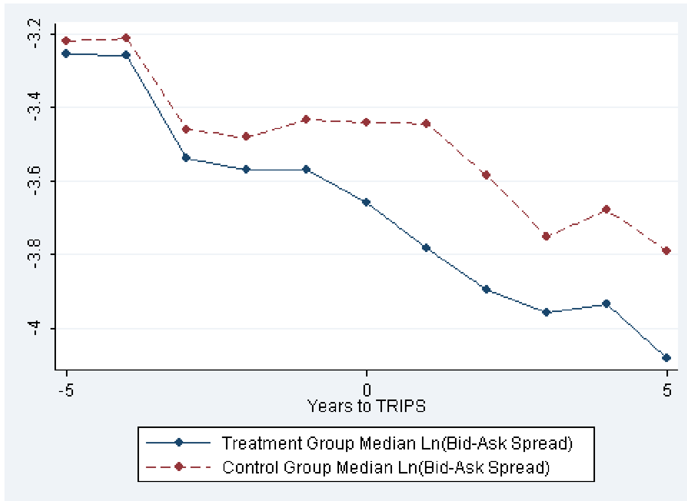


Figure 7: Ln(Bid-Ask Spread) Around TRIPS

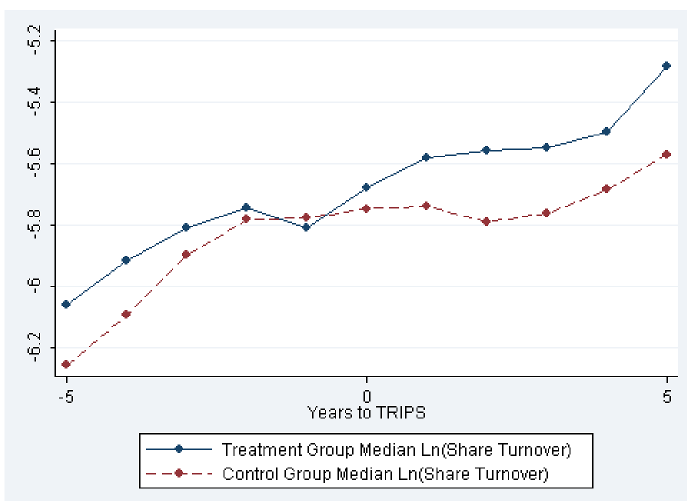


Figure 8: Ln(Share Turnover) Around TRIPS

CHAPTER III

THE IMPACT OF COVENANT VIOLATIONS ON CORPORATE INVESTMENT IN R&D

3.1 Introduction

The economics literature points to technological innovation as a primary source for productivity gains and economic growth (Solow, 1957). As underscored by models of endogenous growth, advances in technology and the knowledge base of the economy stem from the decision of various economic players to make sizable and ongoing investments in R&D (e.g., Romer 1990). About two-thirds of the overall R&D expenditures in the U.S. are made by corporations – as they seek to develop new products and gain a competitive edge.[1] These R&D expenses contribute greatly to the domestic economy: as Baumol (2001) notes, much of the U.S. economic growth can be attributed to significant innovations by established corporations.

Given the vital role innovative firms play, it is important to understand better their access to financing and, in particular, the extent to which their R&D activities can be impeded by capital market frictions. Our focus in the paper is on the impact of debt covenant violations by innovative firms.[2] The concern is that there could be substantial value destruction in the event that financial covenants are violated given the relative absence of tangible assets in these firms. A covenant violation causes

[1]The R&D/GDP ratio of United State was 2.89% as of 2012 `http://www.nsf.gov/statistics/infbrief/nsf14307/`. Commensurately, corporate investment in R&D has a shown a tremendous growth in the last few decades and accounts for approximately 63% of the $428.2 bn in R&D performed in the U.S. in 2011. According to Business R&D and Innovation Survey (BRDIS), which was developed and cosponsored by the National Science Foundation and Census Bureau, "companies spent $294 billion on research and development performed in the United States during 2011, compared with $279 billion during 2010". `http://www.nsf.gov/statistics/infbrief/nsf14307/`.

[2]Banks are a significant source of investment capital for both R&D-intensive and non-R&D-intensive firms (see Houston and James 1996 and Johnson 1997).

control rights to pass to the lender and increases their bargaining power relative to the borrowers. Creditors can use the threat of accelerating the loan to intervene in the firm policies. In the paper, we analyze how covenant violations and the consequent transfer of control rights to lenders impact the R&D expenditures of the firms and their innovative output (patents, citations to patents) after the covenant violations. The key question we address in the paper is whether banks tend to utilize their control rights judiciously to affect improvements in the functioning of R&D intensive firms — or whether they have a short-term orientation and slash R&D expenses, irrespective of their longer-term potential.

A large literature highlights how financial contracts have the ability to mitigate agency problems (Jensen and Meckling (1976); Smith and Warner (1979)) and facilitate financing with the pledging of state-contingent control rights (e.g., Aghion and Bolton (1992); Dewatripont and Tirole (1994)). Covenants are ubiquitous in private loan contracts and violations are not uncommon. These covenant violations, though considered as technical defaults, convey the same contractual rights to creditors as payment defaults and give lenders strong bargaining power allowing them to materially influence violating firm's investment and financial policies (Chava and Roberts (2008); Nini, Smith, and Sufi (2009, 2012)). In the paper, our objective is to better understand how R&D expenditures are affected by the covenant violations and the consequent transfer of control rights to the lender. To our knowledge, we are the first to study lender intervention in firms' R&D policies after a technical covenant violation.

We examine the effect of violations of net worth, tangible net worth or current ratio loan covenants for a comprehensive sample of U.S. borrowers in the LPC Dealscan database. Violations are determined based on when a firm's financial values or ratios fall below the corresponding thresholds imposed by the loan covenants. Focusing on covenant violations also allows us to employ a regression discontinuity design or

RDD (see Chava and Roberts (2008) for a detailed discussion of the institutional features of the covenant violations that make it suitable for a regression discontinuity design.) The application of RDD in this context is appropriate because the treatment (covenant violation) is assigned based on whether the accounting variable falls below the corresponding threshold. Firm-quarters just above and below the threshold are similar except that the latter violate a covenant. Estimates based on the full sample show that R&D expenses are significantly reduced over four and eight quarters after covenant violations. R&D reduces by 1.6% over four quarters and 2.7% over eight quarters after covenant violations. These results are in line with the findings in the literature (see Chava and Roberts, 2008, and Nini, Smith, and Sufi, 2012) for corporate investment.

We also examine a *discontinuity sample* where we exploit this quasi-random assignment of treatment within a narrow band around the threshold, and can identify the local treatment effect of covenant violation on firm policies. In choosing the bandwidth for RDD we rely, in part, on the Imbens and Kalyanaraman's (2012) method. The effect of covenant violations on R&D investment remains statistically significant after imposing a narrow range. The estimated coefficients suggest that covenant violations are associated with a 2% decrease in R&D in four quarters and a 3.7% decrease in eight quarters. This effect is also robust to controlling for firm characteristics. Understandably, the results are stronger for the subsample where R&D is nonzero in the quarter of the covenant violation: a 5% decrease in R&D over four quarters and a 9.3% decrease over eight quarters.

To further show the causal link between creditors' control right and change in R&D investment, we investigate the effect a state level exogenous legislative shocks, the passage of anti-recharacterization statues. These statues strengthen creditor rights over collateral (Mann 2014) and hence would tend to moderate the incentive of banks to intervene in firms' decisions. [3] The anti-recharacterization statutes help creditors avoid the automatic stay by allowing them to transfer collateral to a bankruptcy-remote special-purpose entity. Our results suggest that while R&D decreases significantly after covenant violations, it changes less after the enactment of anti-recharacterization laws that strengthen creditors' right over collateral. This is consistent with creditors becoming less aggressive in intervening in firm's long term investment decisions when they are better protected by state laws.

We have so far shown a causal link between covenant violations and a subsequent decrease in R&D at the violating firm. But its not evident whether the decrease in R&D expenses following covenant violation is in the interests of the firm. It is possible that banks may be more concerned about short term cash flow generation and are unable to discern whether the R&D investment, a long-term investment with uncertain payout, is value enhancing or not. On the other hand, it is possible that creditors identify inefficient investment by the borrowing firm and use their control rights to help improve firm's investment performance. We distinguish between these two hypotheses by examining the circumstances in which creditors cut R&D expenses and what the consequences of their actions are.

We use two proxies for R&D investment efficiency of the firm: Return on Assets (ROA) and a innovative efficiency (see Hirshleifer, Hsu, and Li, 2012; Almeida, Hsu and Li, 2013) as measured by the output (patents) generated by the input (R&D investment). We find that the R&D decrease is concentrated among borrows in which the innovative efficiency is relatively lower and is statistically and economically larger than that found among borrowers where the R&D investment efficiency is higher. Also, in general, among the borrowers with high R&D efficiency, the decline in R&D

[3]The United States imposes an automatic stay requirement that requires the judge's approval for a secured creditor to claim the collateral.

consequent to the covenant violations is indistinguishable from zero.

We next examine whether the cuts in R&D affect shareholders' value by compromising their long term interest. If lenders are judicious in using their control rights, then lenders' action should result in better investment performance. Previous studies by Nini et al. (2012) show that covenant violations are associated with positive subsequent stock market reaction, suggesting that lenders' action adds value to the shareholders. One potential channel is that lenders help improve the efficiency of firm's R&D investment. Supportive of the notion that the R&D expenses are cut judiciously, both in the full sample and in the discontinuity sample, covenant violations are not associated with a significant change in innovation output. This result, combined with the previous results on the change in R&D, suggests that when borrowers violate a loan covenant and the control rights pass to the lenders, lenders reduce firms' R&D investment without affecting their future innovation output and thus improve the efficiency of the firms' R&D investment.

Our paper contributes to various strands of the literature. First, to our knowledge, our paper is the first to document that lenders consider innovative activity of firms ex post in exercising their control rights after covenant violations.[4] We contribute to the literature on the transfer of control rights after technical covenant violations by showing an additional channel, R&D, through which creditors intervene in borrowers' investment policies. Importantly, our results showcase that when innovative borrowers violate their covenants and control rights pass to lenders, these lenders appear to exercise control rights judiciously and differentiate between firms that are performing valuable innovative activity and those that are not. Consequently, there is no drop in innovative output, as measured by patents and citations to patents, after the covenant violations.

[4]e.g. Sweeney (1994), Dichev and Skinner (2002), Chava and Roberts (2008), Nini, Smith, and Sufi (2009, 2012), Liang and Falato (2014), etc.

Second, we contribute to the literature on the financing of innovation.[5] Rajan and Zingales (2003) argue that equity and public debt are more conducive to innovative activity, while bank financing may be better suited to funding more routine projects. However, public markets have their own problems in financing innovative activity. For instance, Holmstrom (1989) argues that public securities may also pressure management to focus on short-term routine projects at the expense of longer-term novel projects. Similarly, the results of Himmelberg and Petersen (1994) are consistent with the view that, because of capital market imperfections, the flow of internal finance is the principal determinant of the rate at which small, high-tech firms acquire technology through R&D. In light of this literature, our results suggest that, at least in some contexts, banks may well be adept at valuing the innovative activity of the firms and efficient at providing capital. Bank lending is an important source of funding for public firms and the fact that lenders exercise their control rights judiciously over R&D policies and don't inefficiently shut down projects means that even firms without *deep pockets* may be able to pursue R&D.

Our paper is also related to the literature that examines the effects of laws, regulations, and governance on innovation. Acharya and Subramanian (2009) find that debtor-friendly bankruptcy laws foster innovation and economic growth, while Acharya, Baghai, and Subramanian (2012) provide evidence that laws that impose restrictions on dismissal of employees encourage innovation and entrepreneurship. Atanassov (2013) highlights the potential for agency problems, showing that the passage of anti-takeover laws shields management from external governance and leads to less innovation. In a somewhat different setting, Seru (2012) finds that firms that are more reliant on internal capital markets produce fewer and less novel patents because

[5]e.g. Kortum and Lerner (2000), Atanassov, Nanda, and Seru (2007), Benfratelloa, Schiantarellic, and Sembenelli (2008), Brown, Fazzari, and Petersen (2009), Lerner, Sorensen, and Stromberg (2011), Tian and Wang (2014), Nanda and Nicholas (2012), Amore, Schneider, and Zaldokas (2013), Chava, Oettl, Subramanian, and Subramanian, (2013), etc.

of agency problems between headquarters and divisional managers. Chava, Oettl, Subramanian, and Subramanian (2013) show that intrastate banking deregulation induced more innovation by young, private firms.

Our paper is also related to a concurrent working paper by Gu, Mao, and Tian (2014) who study the impact of covenant violations on the patent output of the borrowers. They find that there is a significant decrease in patent output after covenant violations. Our results are markedly different from the results documented in their paper that firms' innovation output decreases after covenant violations. But we find that the innovative output as measured by the patents and citations to patents doesn't decrease because banks curtail R&D when the innovative efficiency of the R&D investment is lower. As we point out in detail later in Section 3.4.2, controlling for firm level characteristics, especially firm size is important in this analysis and Gu, Mao and Tian (2014) do not include any firm controls in their specifications. We also highlight several conceptual and methodological reasons for the differences in findings between our paper and Gu, Mao, and Tian (2014). We note that this issue is not just about using R&D or patenting as a measure of the firm level innovation. R&D is partly one of the inputs to the innovation process that drives patenting and we show that banks do in fact curtail excessive R&D. Admittedly, R&D information is missing for a significant fraction of the firms in the COMPUSTAT data (partly due to firms not reporting the expense when it is insignificant). But simply using patent measures of innovation doesn't address this issue because the firms that patent are mostly a subset of firms that report R&D expenses in COMPUSTAT.

The rest of this paper proceeds as follows. Section 3.2 describes the data and the construction of our measures of firm innovation and lender experience along with the description of the bank loan data. Sections 3.3 and 3.4 presents the methodology and the main empirical results. Finally, Section 3.5 concludes.

3.2 Data and Construction of Variables

In this section, we describe the main sources of data used in the paper and detail the construction of the key variables used in the analysis. In particular, there are three main sources of data that we use to construct our sample: (1) Loan Pricing Corporation's (LPC) DealScan for the bank loan data, (2) COMPUSTAT data for firm level accounting information, and (3) The Harvard Patent Network Dataverse for the innovation measures.

We use the dollar-denominated private loans to U.S. firms from the LPC DealScan database. This database provides comprehensive information on private loan pricing and contract terms such as loan amount and maturity, loan purpose, and financial covenants, etc., from 1987 onwards. The information is collected from SEC filings and public documents, lenders, and a staff of reporters. DealScan provides good coverage of loan contracts made to U.S. public firms. According to Carey and Hrycray (1999), the database covers between 50% and 75% of the volume for all commercial and industrial loans in the U.S. The loan data is organized by deal (package) and loan (facility). A package is a contract that may contain multiple loan facilities. Following Chava and Roberts (2008), we focus on deals originated from 1994 onwards when studying covenant violations because information on covenants is limited before 1994.

We collect quarterly accounting information of U.S. public firms from merged CRSP-COMPUSTAT database, excluding financial firms (SIC codes 6000-6999). We then match firm accounting data with DealScan data using Michael Roberts' DealScan-COMPUSTAT Linking Database (See Chava and Roberts, 2008, for details). For each firm-quarter, we find all the packages that are effective and have covenants imposing a minimum level of net worth, tangible net worth, or current ratio. The reason we focus on these three covenants, as discussed by Chava and Roberts (2008), is that these covenants are more frequently used in loan contracts and can be measured without ambiguity. For each firm-quarter, we find the tightest covenant with respect to these three accounting variables from all the effective loans.

In some cases, covenants are dynamic as the threshold is designed to change over time. We follow Chava and Roberts (2008) in dealing with these issues. For dynamic covenants on current ratio that have a starting threshold and an ending threshold, we linearly interpolate the covenant threshold over the life time of the loan. For net worth covenants that adjust with net income, we adjust the covenant threshold based on the end of quarter income and the required fraction of the income for adjustment. For other net worth covenants that require a stock issuance adjustment (a.k.a. "buildup") we exclude them from the sample because DealScan does not provide information on what fraction of stock issuance the threshold should adjust. More details about the data cleaning process are provided in the Appendix B of Chava and Roberts (2008). After merging, we have 28,843 firm-quarter observations for 2,137 firms that are bounded by at least one of the three financial covenants from 1994 to 2011.

The patent data is from the Harvard Patent Network Dataverse.[6] The Harvard Patent Network Dataverse provides information on patents granted from 1975 to 2010 and all the citations made to these patents over the same period (Lai et al., 2013). We merge the patent data with the CRSP-COMPUSTAT using the patent-PERMNO link provided by Noah Stoffman.[7]

The other commonly used data source for the patent data is the NBER patent data. The NBER database provide patent information from 1975 to 2006. The Harvard database update the patent information up to 2010. With the updated version of patent data, we are able to cover a longer period in the empirical analysis. Dass, Nanda, and Xiao (2014) show that the number of patent applications in the patent database is subject to truncation bias towards the end of the sample period and that conventional methods of adjustment do not full close the gap. For that

[6] `http://thedata.harvard.edu/dvn/dv/patent`

[7] `https://iu.app.box.com/patents`

reason, the number of patent applications in the NBER version drops sharply from 2001 to 2006. Using the updated version from Harvard database significantly reduces truncation bias in the number of patent applications in that period. However, the new data is still subject to the same bias for years close to 2010. Other than adjusting the bias following Seru (2014), we ensure the robustness our findings by by dropping the last four years of observations for empirical tests that involve patent data following Dass, Nanda, and Xiao (2014).[8]

A covenant violation takes place when the value of net worth, tangible net worth, or current ratio is below the corresponding threshold imposed by the relevant loan covenant. We define default distance as the difference between these three accounting variables and the corresponding default boundaries. Since our sample is a union set of observations with the three financial covenants, we replace the missing value of distance with respect to one covenant with zero if the observation is bounded by the other covenants. When testing the impact of covenant violations on changes in firm's R&D policy, we control for the first and second power of default distance with respect to these three financial covenants.

We control for firm characteristics that are likely to correlate with covenant violations and firm's R&D policies: *ROA* is operating income divided by total assets; *Market-to-Book* is the market value of equity plus total liability minus deferred taxes and investment tax credit, divided by total assets; *Ln(Assets)* is measured by the natural logarithm of total assets. Firms are more likely to invest in R&D if there is higher operating performance, high market-to-book, and have larger firm size. In addition, we control for the beginning level of R&D, scaled by total assets. We do this in order to control for the mechanical relation between and beginning level and the subsequent change in R&D.

[8]Results are unreported for brevity and are available upon request.

We measure a firm's innovation output based on the log number of patent applications filed in a quarter and the average number of citations on these patents. The number of patent applications, however, is subject to truncation bias because the Harvard Patent Network Dataverse only reports patent grants up to 2010. Patents that have been filed but not yet granted as of 2010 are thus not in the sample. The number of citations is also subject to truncation bias as older patents tend to accumulate more citations compared with newer patents. To adjust for this truncation bias, we follow Seru (2014) and divide the number of patents (citations) for each firm-year by the mean number of patents (citations) or the same patent technology class and year. *repetitive*

Table 25 presents summary statistics for all the variables in the covenant violation analysis. A detailed description of all the variables is provided in the Appendix. We winsorize all the variables at the 1^{st} and 99^{th} percentiles. The fraction of firm-quarters that violate any of the three covenants is 14.1%, which is close to that reported by Chava and Roberts (2008). The statistics of firm characteristics including the three covenant variables are also largely consistent with the literature. The sample mean of *Ln(Assets)* is 5.701, corresponding to 300 million dollars of average total assets. The average R&D expenditure is 1.47 million dollars.

The number of observations for citations and innovative efficiency measures (based on citations and patents) is much smaller than the full sample because these statistics can only be computed for a subset of firms in the sample: there are 4,937 firm-quarter observations that have both non-zero value of R&D as well as number of patents. Among these observations, the innovation efficiency in terms of adjusted number of patents per million dollars of R&D stock has an average of 0.11 with the standard deviation of 0.23, while the similarly measured efficiency based on the adjusted number of citations has an average of 0.28 with the standard deviation of 0.60.

3.3 Empirical Results: R&D Investment Around Covenant Violations

In this section, we investigate lender's actions on firms' R&D policy when firms violate covenants and the control rights pass to lenders. As noted, we focus on financial covenants that impose a minimum level of net worth, tangible net worth, and current ratio. A firm is identified as violating a covenant if the value of any of these three accounting variables in the quarter end is below the closest threshold imposed by the outstanding loans. We then test the following model:

$$\Delta \text{Ln}(\text{R\&D})_{t,t+n} = \alpha_1 + \beta_1 \text{Violation} + \gamma_1{\prime} Control + \gamma_2{\prime} DD + \phi_j + \psi_t + \theta_T + \epsilon, \quad (10)$$

where $\Delta \text{Ln}(\text{R\&D})_{t,t+n}$ is the log change in the R&D expenditure n quarters after violation. We take one plus R&D expenditure to avoid losing observations from taking a natural logarithm of zero. *Violation* is a binary variable that equal 1 if one of the three financial covenants is binding. *Control* refers to control variables including *R&D/Assets*, *ROA*, *Market-to-Book*, and *Ln(Assets)*. *DD* refers the linear and squared default distance with respect to the three covenants. We also include calendar quarter dummies (ψ_t), fiscal quarter dummies (θ_T), and Fama-French 48 industry dummies (ϕ_j) to control for unobserved effects that are invariant within time and industry. We cluster standard errors by firm and quarter following Petersen (2009). This empirical specification resembles the one used by Nini, Smith, and Sufi (2012). By taking a first difference in the dependent variable, we control for firm effects that are invariant over time. Moreover, this specification tests the cumulative effect of covenant violation on R&D policy from the violation quarter over different horizons. Here we focus on the change in R&D over one quarter, one year, and two years from violations.

3.3.1 Full Sample Analysis

Table 26 reports the estimates in the entire sample. We analyze the impact of covenant violations on the log change in the R&D expenditure 1, 4 and 8 quarters after violation in models 1, 2 and 3 respectively. The first column shows the effect of violations on the change in R&D in a quarter after violations is statistically insignificant, suggesting that the impact of creditor control rights over R&D policy does not turn up in the first quarter. This is slightly different from the findings from Chava and Roberts (2008) findings on capital expenditure (CAPEX) as they show that CAPEX decreases immediately after covenant violations. However, this difference is not surprising to the extent that R&D is more stable over time compared with CAPEX and thus may not be adjusted immediately (Hall and Lerner, 2009). Investment in R&D is also very different from investment in capital expenditure. R&D expenditure is not only composed of capital and material costs but also labor. As Hall and Lerner (2009) highlight, in practice majority of R&D expenditure is the wages and salaries of scientists and engineers. The efforts of the scientists and engineers create an intangible asset, the firms' knowledge base, where the profits will be generated. To the extent that this knowledge is embedded in the human capital of the firms' employees, firms will lose the intangible assets if the employees leave or are fired. Hall and Lerner (2009) argue that firms tend to smoothen their R&D expenditure in order to avoid laying off knowledge workers. So, R&D expenditure tend to behave as if it has high adjustment costs and the dynamics can differ from investment in physical assets.

In line with these arguments in Hall and Lerner (2009), estimates in Columns 2 and 3, however, show that the R&D is significantly reduced over four and eight quarters after covenant violations. R&D reduces by 1.6% over four quarters and 2.7% over eight quarters after covenant violations and the effect is statistically significant at least 5% level. The greater magnitude of the coefficient estimate for the eight-quarter change than that for the four-quarter change suggests that cuts in R&D due to covenant violations span beyond one year.

3.3.2 Regression Discontinuity Design

The results in the entire sample are nevertheless subject to endogeneity issues. For example, both covenant violations and decreases in R&D investments may be jointly driven by deteriorating performance. To address the endogeneity concerns, we employ the regression discontinuity design (RDD) to identify the effect of covenant violations on firm's R&D policy following Chava and Roberts (2008). RDD can be applied in this context because treatment (covenant violation in this case) is assigned based on whether the accounting variable falls below the covenant threshold. Firm-quarters that are just above the threshold are comparable to those just below the threshold except that the latter violate a covenant. By exploiting this quasi-random assignment of treatment within a narrow band around the threshold, we can identify the local treatment effect of covenant violation on firm policies.

Chava and Roberts (2008) present a detail discussion on why RDD is an appropriate identification strategy for this question. One potential concern with the RDD design in the context of covenant violations is that the distance from the covenant threshold is not exogenous. It is certainly possible that managers can take action such as manipulating the accounting ratios underlying the covenant thresholds to avoid covenant violations. But relationship lending is a repeated game with the borrowers relying on the relationship lenders over time for various types of loans and services. It is less likely that borrowers can hope to consistently manipulate the accounting ratios without the informed relationship lenders catching up to the manipulation. Moreover, many of the accounting measures underlying the covenants that we consider are non-GAAP.

In line with these arguments, Chava and Roberts (2008) find that proxies of earnings management such as discretionary accrual are not significantly related to the likelihood of covenant violations. According to the survey by Graham, Harvey, and Rajgopal (2005), managers tend to cut investment rather than manipulate the financial reports in order to avoid covenant violations. Such behavior by managers should bias against finding a significant effect of observed covenant violations on subsequent cut in R&D investment. So, as noted by Chava and Roberts (2008), RDD is an appropriate design in the context of covenant violations.

To implement RDD we focus on firm-quarters that fall within a narrow band around the covenant threshold. To determine the bandwidth for RDD, we first use Imbens and Kalyanaraman's (2009) method to estimate the asymptotically optimal bandwidth that minimizes MSE. The estimated bandwidth, in terms of the relative distance between the accounting variable and the corresponding covenant threshold, range from 23% to 52% for the three financial covenants.[9] This is larger than the estimation by Chava and Roberts (2008) who make use of the Silverman's (1986) method. As Imbens et al. (2009) recommend, their estimated bandwidth can be taken as a reference point to assess the sensitivity of estimates to bandwidth choices. Therefore we estimate Model (10) using both 50% bandwidth based on our estimation and 20% bandwidth used by Chava and Roberts (2008). For the local regressions in the discontinuity sample, we do not control for default distances as we do in the entire sample since we already focus on a narrow range of default distances.

We start by graphically present the change in R&D expenditure within a narrow window around the covenant threshold. In Figure 9 we plot the log change in R&D expenditure over different horizon against distance to default measured by the minimum relative distance to the three financial covenant thresholds within the 50% bandwidth. Figure 9a shows that there is a discontinuity in the change of R&D over a quarter around the covenant threshold. There also appear to be a structural shift

[9] We winsorize the default distance at the 5th and 95th percentiles to avoid outliers from driving the bandwidth estimation.

in the one-quarter change of R&D on the two sides of the cutoff. The difference though is somewhat marginal, which is consistent we our earlier analysis and discussion that R&D tend to be smoothen over time and cannot be adjusted immediately. Figure 9b and 9c, however, show a clearer discontinuity in the longer term change of R&D around covenant threshold. The confidence interval of the fitted line shows that the estimated R&D change is significantly lower for firm-quarters right below the covenant threshold compared with those close to but above the threshold. The discrete effect of covenant violation presented in the figure is even sharper for the change in R&D over eight quarters. This is consistent with our the full sample results that covenant violation is associated with a significant decrease in R&D investment which lasts beyond a year.

Table 27 show the results in the discontinuity sample. In Panel A we present estimations in the subsample of firm-quarters within ±50% around the covenant thresholds. Around 40% of observations are removed by imposing this condition. The estimation shows that the effect of covenant violations on R&D change remains statistically significant after imposing a narrow range. The estimated coefficient in Columns 1 and 2 suggest that covenant violations are associated with a 2% decrease in R&D in four quarters and a 3.7% decrease in eight quarters. This effect is also robust to the inclusion of firm characteristics. As shown in Columns 3 and 4, the estimated coefficient on *Violation* remains significant at 5% level when firm characteristics are included.

Panel B shows estimates in the ±20% band following Chava et al. (2008). This window leaves us with around 7,400 observations. This sample size is larger than Chava et al. because first, we use a longer time series (1994-2011); Second, we do not remove firms that never experience a covenant violation over the sample period. The effect again remains significant within this range and the economic magnitude remain similar to the previous estimations. Since a 20% bandwidth leaves us with a reasonable sample size and statistical power, we will use the 20% bandwidth for the subsequent RDD analysis.

In Panel C we raise the bar further and restrict the observations to be within ±10% around the covenant thresholds. After imposing this condition there are around 3,600 observations. The result again shows that covenant violations have a significant negative impact on the change of R&D over the next eight quarters. Moreover, the estimated treat effect is not sensitive to different bandwidth choices. For example, in Column 2 the estimated coefficient for *Violation* varies from -0.0378 to -0.0345 across the three bandwidth choices. These tests together show the robustness of our finding and establish the causal effect of covenant violations on the subsequent R&D investments.

3.3.3 Robustness Check

The sample that we have considered so far includes firms with significant R&D activities and firms without R&D expenses. In another test, we analyze the subsample of firms with some R&D activities in the violation quarters. Other than confirming the robustness of our finding, it also makes sense to focus on R&D firms since creditor intervention in R&D is relevant only when there are some R&D activities to start with. Table 28 present the estimation of Model (10) in the subsample where R&D is nonzero in quarter t. The sample size is reduced substantially, but the effect of covenant violations remain significant. Moreover, the magnitude of the effect becomes stronger – a covenant violation is associated with a 5% decrease in R&D in four quarters and a 9.3% decrease in eight quarters. In the discontinuity sample, the coefficient for *Violation* is significant at 1% level in Column (3) and the coefficient estimate suggests that among firms that are closely lying around the covenant threshold, a violation of covenant will cause a 11% decrease in R&D over eight quarters after violations. Given that a firm cannot cut R&D when has not been any R&D to begin with, these results provide a better estimate of the extent to which lenders intervene in firms' R&D activities after covenant violations.

So far, our empirical specification closely followed Chava and Roberts (2008). One advantage of this approach is that we know which specific covenant was violated and what the distance from the covenant threshold is over time. This also allows us to use the regression discontinuity design that helps in identifying a casual relationship between covenant violations and subsequent R&D investments. On shortcoming of this approach is the limited sample size as we need to rely on the dealscan database for the precise threshold that triggers the covenant violations. An alternate approach that increases the sample size is to consider covenant violations based on the SEC filings.

Finally, we replicate this result using alternative data. Nini, Smith, and Sufi (2012) use records of covenant violations of all non-financial public firms from 1996 to 2007 from the SEC 10-Q and 10-K filings and show that creditors take various actions that improve firm value when a covenant is violated. The data is available on their website.[10] The advantage of the this data is that it covers a broader group of firms, including those without covenant information covered in DealScan. It also covers violation of covenants other than the three financial covenants we focus on using the DealScan data. The disadvantage, however, is that we cannot accurately measure the distance to default in each case because the covenant violations parsed from SEC filings are not specific to any loan or covenant. For the same reason, we are not able to exploit the regression discontinuity design in this setting. Nevertheless, if creditors use the control rights to reduce R&D investment as we predict, we should observe the same pattern in the change of R&D using a broader definition of covenant violation.

[10] `http://faculty.chicagobooth.edu/amir.sufi/data.html`

Hence, we reestimate Model (10) in the sample covered by Nini et al. (2012).[11] Since this SEC filing-based violation data is not specific to any loan or covenant, we can not measure the default distance with respect to any specific covenant. Instead, we control for the level of *Net Worth Ratio* and *Current Ratio* in additional to the firm characteristics we include in the previous analyses. The regression estimates are presented in Table 29. It shows that violations identified in the SEC filings also has a significant negative effect on R&D investment. This further supports the notion that lenders intervene in the R&D investment of violating firms when they takeover the control rights.

3.3.4 Creditor Rights Over Collateral And Action over R&D Investment

To further shows the causal link between creditors' control right and change in R&D investment, we explore creditors' incentive to influence borrower's investment policy. In the event of a technical default, banks monitor and influence borrowers' investment to ensure that creditors' interests are protected. Therefore, an exogenous change in creditor rights may shift their incentive to intervene in firms' decisions.

To test this prediction, we exploit an exogenous legislative shock that strengthens creditor rights over collateral. The United States imposes an automatic stay requirement that requires the judge's approval for a secured creditor to claim the collateral. The anti-recharacterization statutes help creditors avoid the automatic stay by allowing them to transfer collateral to a bankruptcy-remote special-purpose entity. Mann (2014) explores these anti-recharacterization statutes combined with exogenous court decisions that strengthen the role of state property law for patents to show that stronger creditors' rights over patent collateral facilitate the financing of innovation. We follow Mann (2014) and use the staggered enactment of anti-recharacterization

[11] We follow Nini et al. (2012) in filtering the data.

statues in various states to examine the impact on stronger creditor rights over collateral on creditors' action when borrowers violate a loan covenant. We estimate the following model:

$$\Delta \text{Ln(R\&D)}_{t,t+n} = \alpha_2 + \beta_2 \text{Violation} + \beta_3 \text{Violation} \times \text{Post ARL} + \beta_4 \text{Post ARL} + \gamma_3\prime Control + \gamma_4\prime DD + \phi_j + \psi_t + \theta_T + \epsilon, \quad (11)$$

where *Post ARL* is a binary variable that equal 1 after the enactment of anti-recharacterization laws (AR) in the state the firm is located or incorporated.[12] The variable of interest in this model is the interaction term between *Violation* and *Post ARL*. The hypothesis is that if post-violation change in R&D is caused by creditors' intervention to protect their own interest, then with a stronger rights over collateral creditors may be less aggressive in influencing borrowers' investment decision, thus reducing the impact of covenant violation on subsequent R&D change.

We present the estimates of Model (11) in Table 30. The results show that while β_2 remains significantly negative, the estimate of β_3 is significantly positive in both the entire sample (Panel A) and discontinuity sample (Panel B) except in one specification. Moreover, the magnitude of β_3 is close to that of β_2 across specifications. These estimates suggest that while R&D decreases significantly after covenant violations, such decrease is mitigated after the enactment of anti-recharacterization laws that strengthen creditors' right over collateral. This is consistent with our prediction that creditors will be less aggressive in intervening in firm's long term investment decisions when they are better protected by state laws.

3.4 Does Creditor Intervention Enhance Innovative Performance?

So far we have shown that a covenant violation has a causal impact on firm's future R&D investment with R&D investment decreasing up to 8 quarters after the

[12] Table 4 in Mann (2014) provides the states and enactment year of anti-recharacterization laws.

covenant violations. Given the importance of R&D investment to the U.S. economy[13] and the fact that banks are a significant source of capital for investment for both R&D intensive firms and non R&D intensive firms (see Houston and James 1996 and Johnson 1997), it is important to understand the situations in which R&D investments decreases after the covenant violations.

There are two competing hypotheses that can potentially explain this finding. First, it could be that lenders are more concerned about the short term performance and therefore push for better short term performance at the cost of long term investment. Under this hypothesis, lenders' action could undermine the long term interest of shareholders. An alternative explanation is that creditors identify inefficient investment by the borrowing firm and use their control rights to help improve firm's investment performance. To distinguish between these two hypotheses, we examine under what circumstances creditor intervene in R&D investment and what the outcomes of their actions are.

We first check whether the effect of covenant violations vary with firms' operating performance. We again estimate Model (10) with control on firm characteristics in the entire sample and discontinuity sample. This time we allow the coefficient on *Violation* to vary across subsamples with high/low *ROA* prior to violation quarter. The results in Table 31 show that the coefficient on *Violation* is significant only when *ROA* prior to violation quarter is below the sample median. This result holds both in the full sample and discontinuity sample, suggesting that creditors take action on firm's R&D investment only when firms experience low operating performance prior to violations.

[13]One can gauge the importance of R&D to the economy by looking at the rationale for the R&D tax credit is enacted in 1981 and subsequently renewed regularly.

3.4.1 R&D Efficiency and Creditors' Action over R&D Investment

Next we examine the hypothesis that lenders force a cut R&D because they identify inefficient investment when borrowers are violation of a covenant. We measure the efficiency of R&D investment following the literature (Hirshleifer, Hsu, and Li, 2012; Almeida, Hsu and Li, 2013):

$$\begin{aligned}\text{Innovative Efficiency}_t = \text{Innovation Output}_t/(&\text{R\&D}_{t-1} + 0.8 \times \text{R\&D}_{t-2} + 0.6 \times \text{R\&D}_{t-3} \\ &+ 0.4 \times \text{R\&D}_{t-4} + 0.2 \times \text{R\&D}_{t-5}),\end{aligned} \tag{12}$$

where Innovation Output_t is measured by either the adjusted number of patents applied in year t or the adjusted number of citations for patents applied in year t. As mentioned in the Section 3.2, the number of patents and citations are adjusted for truncation bias in the patent data. The denominator is the depreciated sum of R&D expenditure from year $t-1$ to year $t-5$, reflecting the innovation input in the past five years. This ratio measures the amount of innovation output per unit of input and therefore captures the efficiency of a firm's innovative investment. A high value of this measure reflects that R&D investments have been efficient in generating more patents or patents with greater impact. Therefore, we use this measure to judge whether violating firms have been making R&D investments efficiently compared with other firms. We estimate Model (10) and allow the coefficient of *Violation* to vary with the level *Innovative Efficiency* in the year prior to a covenant violation. Since this efficiency measure is relevant only when firms have non-zero R&D expenditure and choose patent their innovation, here we focus on firms that have non-missing value both in the numerator and denominator. This leaves us with around 4,900 observations.

We present the results in Table 32. Columns 1 and 2 of Panel A show that the coefficient of *Violation* is significant only in the *Low Efficiency* subsample measured by patent-R&D ratio, suggesting that lenders tend to curb R&D investment when previous investment has not been efficient in generating patents. In Columns 3 and 4, there is not a significant difference between subsamples with above- and below-median level of citation-based efficiency. A possible explanation is that lenders only focus on the quantity of innovation output in gauging the efficiency of firms' R&D investment. In Panel B, when we focus on the discontinuity sample, most of the coefficients are not significant, possibly due to the lack of statistical power (the sample size is below 1,000). The only exception is in Column 2, where the change in R&D in eight quarters is significant among low efficient subsample. Overall, the results show that creditors tend to cut R&D more when the number of patents applied is low relative to its input prior to a covenant violation.

These results are reassuring for a number of reasons. In general, the financing of R&D investments is complicated by the fact the investments are risky and long-term in nature. Unlike capital expenditures, the output is mostly in intangible assets, specialized to the firm that performs the R&D (see Hall and Lerner 2009). Since lenders mostly prefer to lend against tangible collateral and cash flow, this has led to the view that debt – particularly bank debt – might be unsuitable for the financing of R&D intensive firm (e.g., Rajan and Zingales 2003). A central concern about debt financing of R&D-intensive firms is the potential for considerable value destruction in the event that control passes to the lender. Our results show that lenders are judicious in exercising their control rights and use their enhanced bargaining power to force firms to cut inefficient R&D investment. These results are also in line with the results documented in Chava and Roberts (2008) where the investment cut following covenant violations is concentrated in firms with agency and information problems.

3.4.2 The Effect of Covenant Violations on Innovation Output

Previous tests suggest that lenders differ in their action on the borrowing firm's R&D policy depending on the firm's performance in terms of *ROA* or *Innovative Efficiency*.

These results seem to support the idea that lenders intervene in the R&D investment policy to improve the efficiency of their investment. Another way to test this hypothesis is to look at the outcome of creditor intervention. If lenders are judicious in using their control rights, then lenders' action should result in better investment performance. Previous studies by Nini et al. (2012) show that covenant violations are associated with positive subsequent stock market reaction, suggesting that lenders' action adds value to the shareholders. One potential channel is that lenders help improve the efficiency of firm's R&D investment. To examine this hypothesis, we test the following model to see the impact of covenant violations on firms' innovation output:

$$\Delta \text{Innovation Output}_{t,t+n} = \alpha_3 + \beta_5 \text{Violation} + \gamma_5\prime Control + \gamma_6\prime DD + \phi_j + \psi_t + \theta_T + \epsilon, \tag{13}$$

where ΔInnovation $\text{Output}_{t,t+n}$ is the change in innovation output from quarter t to quarter $t+n$. We measure *Innovation Output* either by the adjusted number of patents applied in that quarter or the total number of citations for patents applied in that quarter. We examine changes in output over three different horizons: four quarters, eight quarters, and twelve quarters since it may take time for the effect of lenders' actions on R&D to turn up in the output. In addition to firm characteristics used in previous regressions, we also control for firms' beginning level of innovation output in the regressions to avoid the mechanical relation between the beginning level and subsequent change in the output. This model resembles Model (10), in which we examine the change in innovation input after covenant violations. Our hypothesis that lenders use control rights to improve firm's R&D efficiency will be rejected if covenant violations result in more decrease in the output relative to the decrease in input.

Table 33 presents our estimation of Model (13). In Panel A we present the estimates in the entire sample. In Columns 1 to 3 (4 to 6) the dependent variable is change in the adjusted number of patents (citations). None of the models shows a significant estimate in the coefficient of *Violation*. In Panel B we present the estimates of the same model in the discontinuity sample, where the absolute value of relative default distance is less than 20% with respect to the three financial covenants. Again we do not find any significant effect of covenant violations on the post-violation change in innovation output.

Figure 10 and 11 plot the change in innovation output against distance to default defined as the minimum relative distance to the three covenant thresholds. In contrast to the change in R&D shown in Figure 9, there is no clear discontinuity in the change in either the number of patent applications or citations just around the covenant threshold. Also there is no significant shift in the change of innovation on the two sides the cutoff other than a few outliers that are well below the threshold. The figures and the regression results, combined with the previous results on the change in R&D, suggests that when borrowers violate a loan covenant and the control rights pass to the lenders, lenders use their enhanced bargaining power to extract a reduction in firms' R&D investment, but this is done without affecting their future innovation output.

We perform several robustness tests on the insignificant effect of covenant violations on innovation output. Firstly, instead of measuring the total number of citations, we use the average number of citations per patent as the outcome variable. The sample size, however, is reduced substantially for this test because the number is missing for firm-quarter observations with zero patent. Nevertheless, we find that covenant violations are not associated with an decrease in the average number of citations per patent subsequently. Secondly, following Dass, Nanda, and Xiao (2014), we drop the patent data between 2007 and 2010 from the regression sample to avoid the results from being driven by the later observations which are subject to truncation bias. Our findings are not changed after dropping those observations. These results are not reported for brevity and are available upon request.

The economics literature points to technological innovation as a primary source for productivity gains and economic growth (Solow, 1957). These advances in technology and the knowledge base require sizable and ongoing investments in R&D, as is underscored by models of endogenous growth (e.g., Romer 1990). Our results suggest that bank financing can be a suitable source of financing even for innovative firms. Even if the bank loans may not always directly finance R&D investment, but bank financing may make funds available for R&D investment by financing other investments of the firm. Our results show that there is a cut in R&D investment following covenant violations in line with the reduction in corporate investment documented in the literature. But creditor intervention improves the efficiency of the firms' R&D investment and there is no decrease in innovation output after the covenant violations.

We note there is a concurrent working paper by Gu, Mao, and Tian (2014) that explores a related question by studying the impact of covenant violations on the innovation output of the firm. However, in contrast to our findings, their finding is that firms' innovation output decreases after covenant violations. They conclude that banks help curtail excessive *investments in innovative projects* that are value-destroying. R&D is one of the inputs to the innovation process that drives patenting and we show that banks do in fact curtail excessive R&D. But we find that the innovative output as measured by the patents and citations to patents doesn't decrease because banks curtail R&D when the innovative efficiency of the R&D investment is lower. We would like to highlight that the debate is not between whether R&D or patenting is a good measure of the innovative activity of the firm. Granted, R&D information is missing for a significant fraction of the firms in the COMPUSTAT data (partly due to firms not reporting the expense when it is insignificant). But using patent measures of innovation doesn't address this issue because the firms that patent are mostly a subset of firms that report R&D expenses in COMPUSTAT. More importantly, conceptually, patenting is partly the output of innovation activities at the firm and it doesn't happen in vaccuum. A significant fraction of R&D expenditure is the wages and salaries of scientists and engineers (see Hall and Lerner (2009)) and hence R&D spending is a critical input to the innovation activities at the firm and that may lead to patenting output at the firm. R&D is a firm policy that is the direct observable action of creditor intervention. Patents on the other hand are an outcome affected by many other factors. Its also not clear why there is an abrupt drop in the patent output around covenant violations as one would expect that there would be a lag after the covenant violations in the patents applied.

Apart from the aforementioned reasons, there are several methodological reasons for the differences in findings between our paper and Gu, Mao, and Tian (2014). First, their main empirical specification is propensity score matching (PSM) with the SEC filing-based violation data provided by Nini et al. while we use the regression discontinuity design (RDD) based on specific financial covenant thresholds from DealScan and based on Chava and Roberts (2008). More importantly, in the one set of results presented by Gu et al. (2014) where they apply RDD to the Dealscan-based covenant data, they do not control for any observable firm characteristics in the discontinuity sample. It is important to control for firm level characteristics, especially size of the firm (that is highly correlated with the patenting) in order to reduce the omitted variable bias. Finally, in all of their empirical tests, they control for the fixed effects of 12 Fama-French industries and use the level of innovation output as the dependent variable. This specification does not fully account for the heterogeneity across firms that is invariant over time. In our specification we account for this effect by taking the first difference of our dependent variables. An alternative way is to control for firm fixed effects in the regression. In the unreported tests where we use the level of R&D expenditure or innovation output as dependent variables with the inclusion of firm fixed effect, we find that R&D decreases after covenant violations but the number of patents (or citations) do not. This result holds using either DealScan-based violations or SEC filing-based violations. The results are available upon request.

3.5 Conclusion

Corporate investment in R&D is an important ingredient of innovation and economic growth. But R&D is a long-term investment with a uncertain payout and is mostly intangible. In this paper, we shed light on whether banks, an important source of debt capital for firms, are discerning with respect to the R&D projects of the firm. Understanding the efficacy of bank financing of innovative firms is important: Intellectual property (IP) and its creation contribute enormously to the value of many public firms and the broader economy. Specifically, we investigate the consequences of a loan covenant violation by the borrowing firm.

Violations of financial covenants in bank loans contracts lead to technical defaults and a shift of control rights to the creditor and increase their bargaining power. Lenders can then use the threat of accelerating the loan to extract concessions and/or compel the borrowers to follow her preferred course of action. We contribute to the literature on covenant violations by showing that an important corporate policy such as R&D investment is also affected by the covenant violations.

Our results support the notion that banks, on the whole, appear to be discerning in terms of the changes they require of the borrowing firms. There is a significant decrease in R&D following covenant violations, but the decline seems to be concentrated in firms with a lower innovative efficiency. Consequently, while there is a significant cut back in R&D expenses, it does not appear to come at the expense of innovative output. Our results support the view that bank financing can be a viable source of financing for R&D intensive firms.

Table 25: Summary Statistics for Chapter 3

This panel presents summary statistics of the main variables used in our analyses. We winsorize all the variables at the 1st and 99th percentiles. All the variables are defined in the Appendix.

	N	**Mean**	**Median**	**Std. Dev.**
Violation	28843	0.141	0.000	0.348
ROA	28843	0.031	0.032	0.040
Market-to-Book	28843	1.684	1.314	1.183
Ln(Assets)	28843	5.701	5.606	1.677
Net Worth	28843	519.741	126.379	1285.990
Tangible Net Worth	28637	509.667	125.527	1256.408
Current Ratio	28641	2.323	1.903	1.648
Ln(R&D)	28843	0.386	0.000	0.878
Ln(Patent)	28378	0.077	0.000	0.274
Ln(Citation)	28378	0.136	0.000	0.531
Innovative Efficiency (Patent)	4937	0.108	0.039	0.230
Innovative Efficiency (Citation)	4924	0.279	0.092	0.592

Table 26: Change in R&D After Covenant Violations

In this table we examine whether lenders cut R&D after covenant violations. The sample consists of firm-quarter observations of non-financial firms from the CRSP-Compustat merged database that have effective covenants restricting the current ratio, net worth, or tangible net worth. We present estimates from regressions where the dependent variable is $\Delta Ln(R\&D)_{t,t+n}$, the log difference in the R&D expenditure between violation quarter and n quarters later. The independent variable of interest is *Violation*, a binary variable that equal 1 if one of the three financial covenants is binding. Firm characteristics including *R&D/Assets*, *ROA*, *Market-to-Book*, *Ln(Assets)*, and linear and squared default distance with respect to the three covenants are included in the regressions. Calendar quarter dummies, fiscal quarter dummies and industry dummies are also included. t-statistics using standard errors clustered by firm and calendar quarter are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variable:	$\Delta Ln(R\&D)_{t,t+1}$	$\Delta Ln(R\&D)_{t,t+4}$	$\Delta Ln(R\&D)_{t,t+8}$
	(1)	(2)	(3)
Violation	-0.0113	-0.0158***	-0.0274**
	(-1.55)	(-2.65)	(-2.53)
R&D/Assets	-9.1813***	-3.3835***	-5.9850***
	(-9.19)	(-9.26)	(-9.36)
ROA	-0.7391***	0.2347***	0.4181***
	(-5.88)	(3.92)	(3.16)
Market-to-Book	0.0342***	0.0228***	0.0330***
	(8.18)	(8.14)	(6.48)
Ln(Assets)	-0.0082	-0.0043***	-0.0132***
	(-1.31)	(-2.71)	(-3.98)
Observations	28840	28380	27654
Adjusted R^2	0.150	0.069	0.080
Industry Dummies	✓	✓	✓
Fiscal Quarter Dummies	✓	✓	✓
Calendar Quarter Dummies	✓	✓	✓
Default Distance (1st & 2nd power)	✓	✓	✓

Table 27: Change in R&D After Covenant Violations: Discontinuity Sample

In this table we examine whether lenders cut R&D after covenant violations. The sample consists of firm-quarter observations of non-financial firms from the CRSP-Compustat merged database that have effective covenants restricting the current ratio, net worth, or tangible net worth and that the default distance with respect to these covenants is within a narrow bandwidth. Specifically, in Panels A, B, and C the absolute value of the relative distance to the covenant threshold is less than 50%, 20% , and 10%, respectively. We present estimates from regressions where the dependent variable is $\Delta Ln(R\&D)_{t,t+n}$, the log difference in the R&D expenditure between violation quarter and n quarters later. The independent variables of interest is *Violation*, which is a binary variable that equal 1 if one of the three financial covenants is binding. In Columns 3 and 4 firm characteristics including *R&D/Assets*, *ROA*, *Market-to-Book*, *Ln(Assets)* are included in the regressions. Calendar quarter dummies, fiscal quarter dummies and industry dummies are also included. *t*-statistics using standard errors clustered by firm and calendar quarter are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variable:	$\Delta Ln(R\&D)_{t,t+4}$	$\Delta Ln(R\&D)_{t,t+8}$	$\Delta Ln(R\&D)_{t,t+4}$	$\Delta Ln(R\&D)_{t,t+8}$
	(1)	(2)	(3)	(4)
		Panel A: Bandwidth=50%		
Violation	-0.0201***	-0.0378***	-0.0121**	-0.0209**
	(-3.95)	(-3.91)	(-2.36)	(-2.48)
Observations	17167	16826	14589	14286
Adjusted R^2	0.012	0.015	0.073	0.094
		Panel B: Bandwidth=20%		
Violation	-0.0127**	-0.0345***	-0.0108*	-0.0282***
	(-2.01)	(-3.04)	(-1.68)	(-3.06)
Observations	7486	7354	6401	6285
Adjusted R^2	0.005	0.016	0.065	0.098
		Panel C: Bandwidth=10%		
Violation	-0.0120	-0.0372**	-0.0104	-0.0291**
	(-1.46)	(-2.56)	(-1.15)	(-2.53)
Observations	3612	3540	3093	3034
Adjusted R^2	-0.003	0.025	0.062	0.123
Firm Controls			✓	✓
Industry Dummies	✓	✓	✓	✓
Fiscal Quarter Dummies	✓	✓	✓	✓
Calendar Quarter Dummies	✓	✓	✓	✓

Table 28: Non-zero R&D Sample

This table replicates the baseline results in the subsample with non-zero R&D in the violation quarter. Firm characteristics including *R&D/Assets*, *ROA*, *Market-to-Book*, *Ln(Assets)*, and linear and squared default distance with respect to the three covenants are included in the regressions. In Panel B the absolute value of the relative distance to the covenant threshold is less than 20%. Calendar quarter dummies, fiscal quarter dummies and industry dummies are also included. *t*-statistics using standard errors clustered by firm and calendar quarter are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Panel A: Subsample with Non-zero R&D

Dependent Variable:	$\Delta Ln(R\&D)_{t,t+4}$ (1)	$\Delta Ln(R\&D)_{t,t+8}$ (2)
Violation	-0.0507**	-0.0932**
	(-2.25)	(-2.32)
Observations	7213	7097
Adjusted R^2	0.116	0.108
Firm Controls	✓	✓
Industry Dummies	✓	✓
Fiscal Quarter Dummies	✓	✓
Calendar Quarter Dummies	✓	✓
Default Distance (1st & 2nd power)	✓	✓

Panel B: Discontinuity Sample with Non-zero R&D

Dependent Variable:	$\Delta Ln(R\&D)_{t,t+4}$ (1)	$\Delta Ln(R\&D)_{t,t+8}$ (2)
Violation	-0.0295	-0.1113***
	(-0.95)	(-2.72)
Observations	1327	1314
Adjusted R^2	0.106	0.108
Firm Controls	✓	✓
Industry Dummies	✓	✓
Fiscal Quarter Dummies	✓	✓
Calendar Quarter Dummies	✓	✓

Table 29: Covenant Violation Based on SEC Filings

This table replicates the main result using SEC filing-based covenant violation data provided by Nini, Smith, and Sufi (2012). Firm characteristics including *R&D/Assets*, *ROA*, *Market-to-Book*, *Ln(Assets)*, *Networth Ratio*, and *Current Ratio* are included in the regressions. Calendar quarter dummies, fiscal quarter dummies and industry dummies are also included. t-statistics using standard errors clustered by firm and calendar quarter are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variable:	$\Delta Ln(R\&D)_{t,t+4}$ (1)	$\Delta Ln(R\&D)_{t,t+8}$ (2)
Violation	-0.0151***	-0.0157***
	(-3.32)	(-2.73)
R&D/Assets	-2.5792***	-4.4529***
	(-16.16)	(-17.63)
ROA	0.1254***	0.1687**
	(2.92)	(2.31)
Market-to-Book	0.0249***	0.0392***
	(20.61)	(17.84)
Ln(Assets)	-0.0038***	-0.0117***
	(-3.50)	(-6.18)
Networth Ratio	0.0262***	0.0323***
	(4.20)	(2.88)
Current Ratio	0.0032***	0.0036***
	(5.28)	(3.23)
Observations	143224	143222
Adjusted R^2	0.077	0.092
Industry Dummies	✓	✓
Fiscal Quarter Dummies	✓	✓
Calendar Quarter Dummies	✓	✓

Table 30: Anti-recharacterization Laws and Change in R&D After Covenant Violations

We present estimates from regressions where the dependent variable is $\Delta Ln(R\&D)_{t,t+n}$, the log difference in the R&D expenditure between violation quarter and n quarters later. The independent variable of interest is the interaction term between *Violation* and a binary variable that equal 1 after the enactment of anti-recharacterization laws (AR) in the state the firm is located or incorporated. In Panel A the sample consists of firm-quarter observations of non-financial firms from the CRSP-Compustat merged database that have effective covenants restricting the current ratio, net worth, or tangible net worth. Panel B presents the results for the discontinuity sample, where the absolute value of the relative distance to the covenant threshold is less than 20%. Firm characteristics including *R&D/Assets*, *ROA*, *Market-to-Book*, *Ln(Assets)* are included in the regressions. In Panel A the linear and squared default distance with respect to the three covenants are included. Calendar quarter dummies, fiscal quarter dummies, industry dummies, location state and incorporation state dummies are also included. *t*-statistics using standard errors clustered by firm and calendar quarter are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Panel A: Entire Sample

Dependent Variable:	$\Delta Ln(R\&D)_{t,t+4}$ (1)	$\Delta Ln(R\&D)_{t,t+8}$ (2)
Violation	-0.0246***	-0.0383***
	(-3.40)	(-2.85)
Violation × Post AR	0.0215***	0.0196
	(2.67)	(1.09)
Post AR	0.0022	0.0033
	(0.38)	(0.23)
Observations	27734	27038
Adjusted R^2	0.072	0.085
Firm Controls	✓	✓
Industry Dummies	✓	✓
Fiscal Quarter Dummies	✓	✓
Calendar Quarter Dummies	✓	✓
Default Distance (1st & 2nd power)	✓	✓
Incorporation State Dummies	✓	✓
Headquarter State Dummies	✓	✓

Panel B: Discontinuity Sample

Dependent Variable:	$\Delta Ln(R\&D)_{t,t+4}$ (1)	$\Delta Ln(R\&D)_{t,t+8}$ (2)
Violation	-0.0181*	-0.0469***
	(-1.93)	(-3.81)
Violation × Post AR	0.0206*	0.0447**
	(1.87)	(2.45)
Post AR	0.0063	0.0101
	(0.51)	(0.42)
Observations	6358	6244
Adjusted R^2	0.066	0.111
Firm Controls	✓	✓
Industry Dummies	✓	✓
Fiscal Quarter Dummies	✓	✓
Calendar Quarter Dummies	✓	✓
Incorporation State Dummies	✓	✓
Headquarter State Dummies	✓	✓

Table 31: Operating Performance and Change in R&D After Covenant Violations

We present estimates from regressions where the dependent variable is $\Delta Ln(R\&D)_{t,t+n}$, the log difference in the R&D expenditure between violation quarter and n quarters later. The independent variables of interest are the interaction term between *Violation* and binary variables indicating high/low ROA in the quarter prior to covenant violation. In Panel A the sample consists of firm-quarter observations of non-financial firms from the CRSP-Compustat merged database that have effective covenants restricting the current ratio, net worth, or tangible net worth. Panel B presents the results for the discontinuity sample, where the absolute value of the relative distance to the covenant threshold is less than 20%. Firm characteristics including *R&D/Assets*, *ROA*, *Market-to-Book*, *Ln(Assets)* are included in the regressions. In Panel A the linear and squared default distance with respect to the three covenants are included. Calendar quarter dummies, fiscal quarter dummies and industry dummies are also included. *t*-statistics using standard errors clustered by firm and calendar quarter are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Panel A: Entire Sample

Dependent Variable:	$\Delta Ln(R\&D)_{t,t+4}$ (1)	$\Delta Ln(R\&D)_{t,t+8}$ (2)
Violation × Low ROA	-0.0240***	-0.0421***
	(-3.65)	(-3.37)
Violation × High ROA	-0.0074	-0.0142
	(-0.94)	(-0.99)
High ROA	-0.0013	-0.0039
	(-0.37)	(-0.53)
Observations	28185	27459
Adjusted R^2	0.068	0.079
Firm Controls	✓	✓
Industry Dummies	✓	✓
Fiscal Quarter Dummies	✓	✓
Calendar Quarter Dummies	✓	✓
Default Distance (1st & 2nd power)	✓	✓

Panel B: Discontinuity Sample

Dependent Variable:	$\Delta Ln(R\&D)_{t,t+4}$ (1)	$\Delta Ln(R\&D)_{t,t+8}$ (2)
Violation × Low ROA	-0.0143*	-0.0419***
	(-1.84)	(-3.57)
Violation × High ROA	-0.0084	-0.0137
	(-1.10)	(-1.18)
High ROA	0.0049	-0.0102
	(0.86)	(-0.86)
Observations	6393	6277
Adjusted R^2	0.064	0.100
Firm Controls	✓	✓
Industry Dummies	✓	✓
Fiscal Quarter Dummies	✓	✓
Calendar Quarter Dummies	✓	✓

Table 32: Innovative Efficiency and Change in R&D After Covenant Violations

We present estimates from regressions where the dependent variable is $\Delta Ln(R\&D)_{t,t+n}$, the log difference in the R&D expenditure between violation quarter and n quarters later. The independent variables of interest are the interaction term between *Violation* and binary variables indicating high/low *Innovative Efficiency* in the year prior to covenant violation. In Panel A the sample consists of firm-quarter observations of non-financial firms from the CRSP-Compustat merged database that have effective covenants restricting the current ratio, net worth, or tangible net worth. Panel B presents the results for the discontinuity sample, where the absolute value of the relative distance to the covenant threshold is less than 20%. Firm characteristics including *R&D/Assets*, *ROA*, *Market-to-Book*, *Ln(Assets)* are included in the regressions. In Panel A the linear and squared default distance with respect to the three covenants are included. Calendar quarter dummies, fiscal quarter dummies and industry dummies are also included. *t*-statistics using standard errors clustered by firm and calendar quarter are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Panel A: Entire Sample

Innovative Efficiency based on:	Patent		Citation	
Dependent Variable:	$\Delta Ln(R\&D)_{t,t+4}$	$\Delta Ln(R\&D)_{t,t+8}$	$\Delta Ln(R\&D)_{t,t+4}$	$\Delta Ln(R\&D)_{t,t+8}$
	(1)	(2)	(3)	(4))
Violation × Low Efficiency	-0.0748**	-0.1412**	-0.0561*	-0.1218*
	(-2.37)	(-2.16)	(-1.66)	(-1.87)
Violation × High Efficiency	-0.0516	-0.0937	-0.0714**	-0.1238**
	(-1.53)	(-1.61)	(-2.27)	(-2.12)
High Efficiency	-0.0032	0.0408	0.0300*	0.0436
	(-0.20)	(1.27)	(1.93)	(1.40)
Observations	4937	4928	4924	4917
Adjusted R^2	0.127	0.106	0.128	0.106
Firm Controls	✓	✓	✓	✓
Industry Dummies	✓	✓	✓	✓
Fiscal Quarter Dummies	✓	✓	✓	✓
Calendar Quarter Dummies	✓	✓	✓	✓
Default Distance (1st & 2nd power)	✓	✓	✓	✓

Panel B: Discontinuity Sample

Innovative Efficiency based on:	Patent		Citation	
Dependent Variable:	$\Delta Ln(R\&D)_{t,t+4}$	$\Delta Ln(R\&D)_{t,t+8}$	$\Delta Ln(R\&D)_{t,t+4}$	$\Delta Ln(R\&D)_{t,t+8}$
	(1)	(2)	(3)	(4)
Violation × Low Efficiency	-0.0423	-0.1373**	-0.0116	-0.0955
	(-1.02)	(-2.16)	(-0.41)	(-1.49)
Violation × High Efficiency	-0.0166	-0.0699	-0.0495	-0.1235
	(-0.44)	(-0.94)	(-1.28)	(-1.61)
High Efficiency	-0.0174	-0.0566	0.0246	-0.0137
	(-0.39)	(-0.66)	(0.44)	(-0.17)
Observations	937	937	933	933
Adjusted R^2	0.151	0.113	0.152	0.110
Firm Controls	✓	✓	✓	✓
Industry Dummies	✓	✓	✓	✓
Fiscal Quarter Dummies	✓	✓	✓	✓
Calendar Quarter Dummies	✓	✓	✓	✓

Table 33: Change in Innovation Output After Covenant Violations

In Columns 1 to 3 (4 to 6) the dependent variable is $\Delta Ln(Patent)_{t,t+n}$ ($\Delta Ln(Citation)_{t,t+n}$), the log difference in the number of patents (citations per patent) between violation quarter and n quarters later. The independent variables of interest is *Violation*. In Panel A the sample consists of firm-quarter observations of non-financial firms from the CRSP-Compustat merged database that have effective covenants restricting the current ratio, net worth, or tangible net worth. Panel B presents the results for the discontinuity sample, where the absolute value of the relative distance to the covenant threshold is less than 20%. Firm characteristics including $\Delta Ln(Patent)_t$ (or $\Delta Ln(CitationsperPatent)_t$), *R&D/Assets*, *ROA*, *Market-to-Book*, and *Ln(Assets)* are included in the regressions. In Panel A the linear and squared default distance with respect to the three covenants are included. Calendar quarter dummies, fiscal quarter dummies and industry dummies are also included. t-statistics using standard errors clustered by firm and calendar quarter are in brackets. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Panel A: Entire Sample

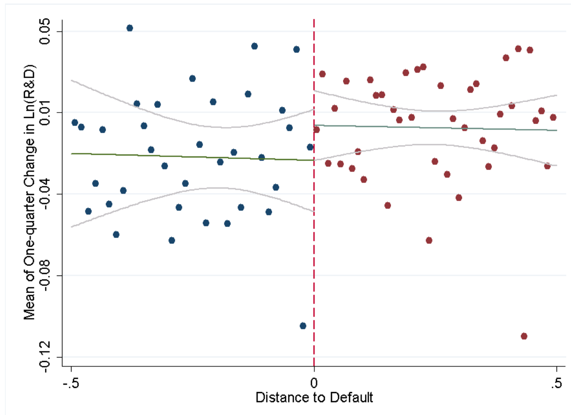
Dependent Variable:	$\Delta Ln(Patent)_{t,t+n}$			$\Delta Ln(Citation)_{t,t+n}$		
$n =$	4	8	12	4	8	12
	(1)	(2)	(3)	(4)	(5)	(6)
Violation	-0.0060	-0.0051	-0.0019	-0.0030	-0.0019	-0.0039
	(-1.46)	(-1.06)	(-0.32)	(-0.41)	(-0.23)	(-0.38)
$Ln(Patent)_t$	-0.4076***	-0.4672***	-0.5306***			
	(-20.36)	(-23.36)	(-21.62)			
$Ln(Citation)_t$				-0.4267***	-0.4967***	-0.5817***
				(-24.89)	(-26.97)	(-24.66)
R&D/Assets	0.6573***	0.7031***	0.6669***	1.3567***	1.2430***	0.9733**
	(4.59)	(4.02)	(3.38)	(4.89)	(3.38)	(2.27)
ROA	0.0587*	0.1020***	0.1429***	0.1315*	0.2335***	0.2470***
	(1.74)	(2.75)	(3.39)	(1.86)	(2.94)	(2.82)
Market-to-Book	0.0038**	0.0058***	0.0085***	0.0077**	0.0108***	0.0134***
	(2.53)	(2.76)	(3.47)	(2.51)	(2.76)	(3.16)
Ln(Assets)	0.0133***	0.0120***	0.0106***	0.0220***	0.0193***	0.0171***
	(8.32)	(6.68)	(5.24)	(8.91)	(6.27)	(4.72)
Observations	27663	26852	25944	27663	26852	25944
Adjusted R^2	0.386	0.451	0.513	0.348	0.426	0.519
Industry Dummies	✓	✓	✓	✓	✓	✓
Fiscal Quarter Dummies	✓	✓	✓	✓	✓	✓
Calendar Quarter Dummies	✓	✓	✓	✓	✓	✓
Default Distance (1st & 2nd power)	✓	✓	✓	✓	✓	✓

Panel B: Discontinuity Sample

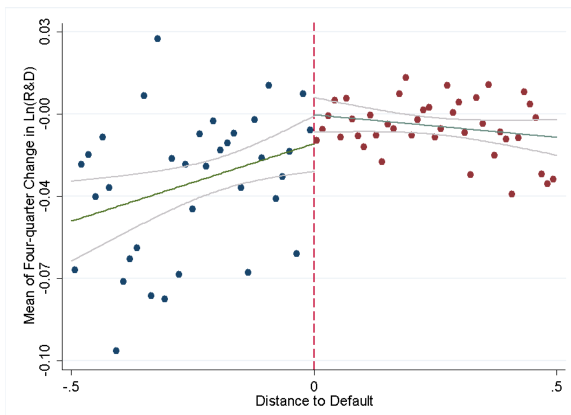
Dependent Variable:	$\Delta Ln(Patent)_{t,t+n}$			$\Delta Ln(Citation)_{t,t+n}$		
$n =$	4	8	12	4	8	12
	(1)	(2)	(3)	(4)	(5)	(6)
Violation	-0.0027	-0.0032	0.0032	-0.0013	-0.0034	-0.0030
	(-0.77)	(-0.77)	(0.56)	(-0.20)	(-0.45)	(-0.32)
Observations	6289	6149	5994	6289	6149	5994
Adjusted R^2	0.433	0.506	0.567	0.412	0.475	0.588
Firm Controls	✓	✓	✓	✓	✓	✓
Industry Dummies	✓	✓	✓	✓	✓	✓
Fiscal Quarter Dummies	✓	✓	✓	✓	✓	✓
Calendar Quarter Dummies	✓	✓	✓	✓	✓	✓

Figure 9: Log change in R&D expenditure within 50% bandwidth of distance to default.

(a) One-quarter Change in Ln(R&D)



(b) Four-quarter Change in Ln(R&D)



(c) Eight-quarter Change in Ln(R&D)

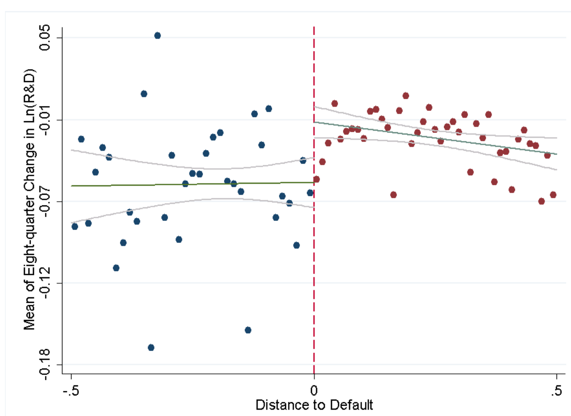
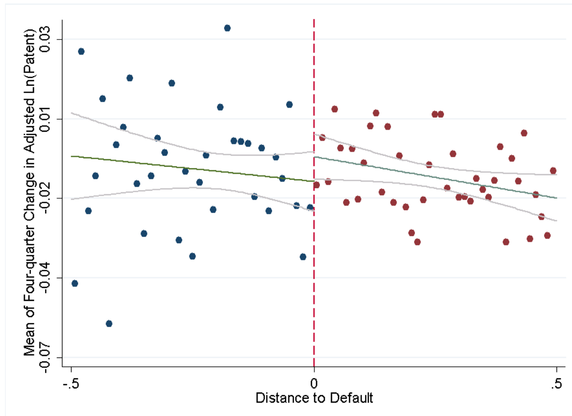
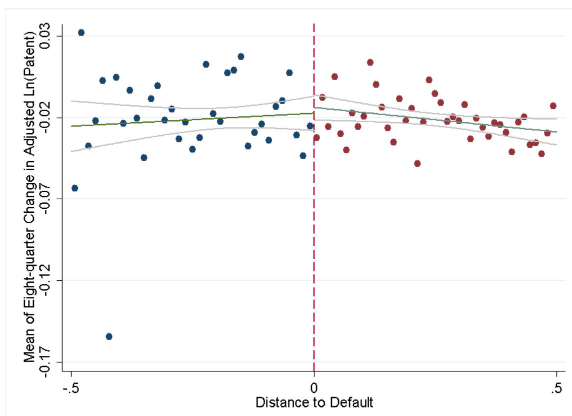


Figure 10: Log change in the adjusted number of patents within 50% bandwidth of distance to default.

(a) Four-quarter Change in Ln(Patent)



(b) Eight-quarter Change in Ln(Patent)



(c) Twelve-quarter Change in Ln(Patent)

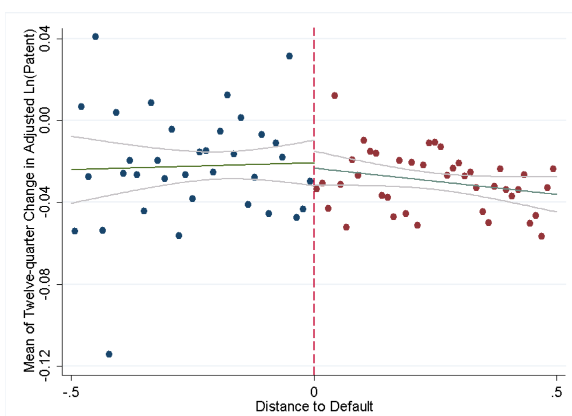
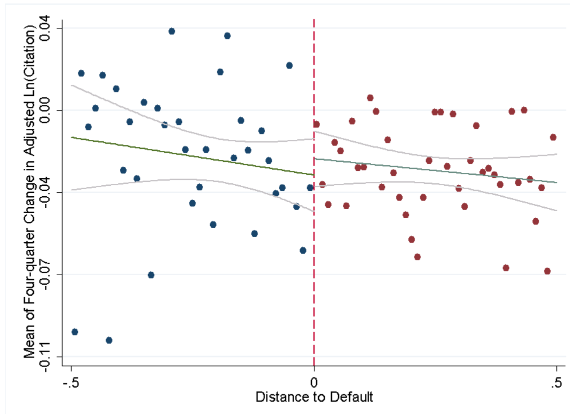
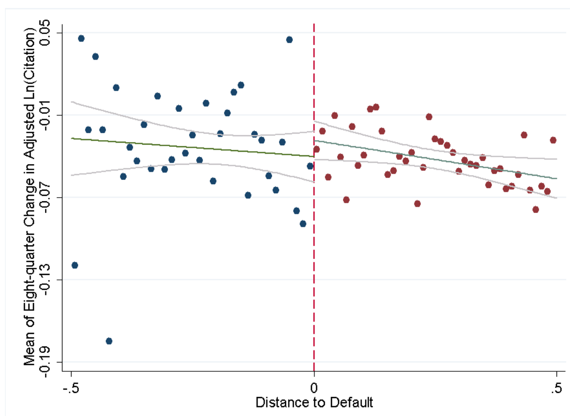


Figure 11: Log change in the adjusted total number of citations within 50% bandwidth of distance to default.

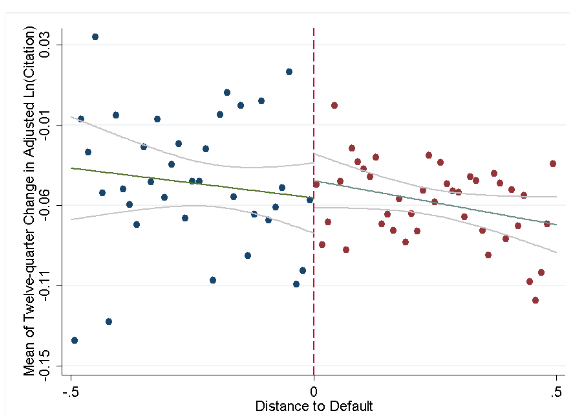
(a) Four-quarter Change in Ln(Citation)



(b) Eight-quarter Change in Ln(Citation)



(c) Twelve-quarter Change in Ln(Citation)



APPENDIX A

VARIABLE DEFINITION FOR CHAPTER 1

- *Patent* is the number patent applications. To adjust for truncation bias, we back out the truncated portion of patent applications based on the historical distribution using Equation (1) for the number of applications from 2004 to 2007.
- *Citation* is the number citations on the applied patents. We use the adjustment factor provided by Hall et al. to adjust the number of citations for truncation bias.
- *Pressure*: For each firm-quarter, we calculate the net fund flow-driven trade as:

  $$\frac{\Sigma_k(max(0, \Delta Holdings_{i,k,t})|Flow_{k,t} > 90^{th}pctl.) - (max(0, -\Delta Holdings_{i,k,t})|Flow_{k,t} < 10^{th}pctl.)}{SharesOutstanding_{i,t-1}}.$$

  We assign a variable for each firm-quarter that equals to 1 if the net fund flow-driven trade calculated above is positive, -1 if the net fund flow-driven trade is negative, and 0 otherwise. *Pressure* for each fiscal year is measured as the absolute value of the average of this indicator variable across the four quarters.
- *Positive Pressure*: For each firm-quarter, we assign a variable for each firm-quarter that equals to 1 if the net fund flow-driven trade is positive, and 0 otherwise. *Positive Pressure* for each fiscal year is measured as the average of this indicator variable of the four quarters.
- *Negative Pressure*: For each firm-quarter, we assign a variable for each firm-quarter that equals to 1 if the net fund flow-driven trade is negative, and 0 otherwise. *Negative Pressure* for each fiscal year is measured as the average of this indicator variable of the four quarters.
- *Ln(R&D)* is the natural logarithm of the firm's R&D expenditure.
- *Ln(Assets)* is the natural logarithm of total assets.
- *Leverage* is the sum of long term debt and debt in current liabilities divided by total assets.
- *ROA* is equal to earnings before extraordinary items divided by lagged asset .
- *Q* is the sum of total assets and the difference between market value and book value of total common equity, divided by total assets.

- *SA Index* is equal to $-0.737 \times Ln(Assets) + 0.043 \times (Ln(Assets))^2 - (0.040 * Age)$ where $Assets$ is the total assets in billions of 2004 dollar and winsorized at \$4.5 billion and Age is winsorized at 37 years.

- *CAPEX* is the capital expenditure divided by lagged total assets.

- *Ln(K/L)* is the natural logarithm of total assets divided by number of employees.

- *Tangibility* is the net total value of property, plant and equipment, divided by total assets.

- *Ln(Ret Volatility)* is the natural logarithm of the standard deviation of daily stock returns in the fiscal year.

- *Herfindahl* is the Herfindahl index of an industry defined by 4-digit SIC.

- *Absolute Earnings Announcement CAR* is the absolute value of average CAR from day -2 to day 2 around earnings announcements.

- *PIN* is the probability of informed trading following Duarte and Young (2009).

- *Absolute Stock Corr. with Peer Firms* is the absolute value of correlation between the monthly stock return of the firm with the average monthly stock return of peer firms over the fiscal year.

- *WW Index* is equal to $-0.091 \times \frac{CashFlow}{Assets} - 0.062 \times I(CashDividendDummy > 0) + 0.021 \times \frac{LongTermDebt}{Assets} - 0.044 \times Ln(Assets) + 0.102 \times$ 3-digit SIC Industry Growth $- 0.035 \times$ (Sales Growth).

- *Wealth-Performance Sensitivity* is the scaled CEO wealth-performance sensitivity following Edmans, Gabaix and Landier (2009).

- *Blockholder Dummy* is a binary variable that is equal to one if there is at least one blockholder that has a minimum of 5% equity ownership in the firm, and zero otherwise.

- *Shorter Investor Ownership* is the number of shares held by transient investors (Bushee, 1998), divided the total number of the firm's shares outstanding.

- *Long Investor Ownership* is the number of shares held by dedicated investors and quasi-indexers (Bushee, 1998), divided the total number of the firm's shares outstanding.

APPENDIX B

VARIABLE DEFINITION FOR CHAPTER 2

- *Treated*: is a binary variable that equals to 1 if the firm has applied for patents in 1993 or 1994 and 0 otherwise.
- *Ln(Amihud)* is defined as $ln(1+AvgILLIQ\times 10^9)$, where $AvgILLIQ$ is an yearly average of illiquidity measured as the absolute return divided by dollar trading volume:$AvgILLIQ_{i,t} = \frac{1}{Days_{i,t}}\sum_{d=1}^{Days_{i,t}}\frac{|R_{i,t,d}|}{DolVol_{i,t,d}}$ where $Days_{i,t}$ is the number of valid observation days for stock i in fiscal year t, and $R_{i,t,d}$ and $DolVol_{i,t,d}$ are the return and dollar trading volume of stock i on day d in the fiscal year t.
- *Ln(Bid-Ask Spread)* is defined as $ln(Bid-Ask\ Spread_{i,t})$ where where $Bid-Ask\ Spread_{i,t} = \frac{1}{Days_{i,t}}\sum_{d=1}^{Days_{i,t}}\frac{Ask_{i,t,d}-Bid_{i,t,d}}{(Ask_{i,t,d}+Bid_{i,t,d})/2}$ where $Days_{i,t}$ is the number of observations for stock i in fiscal year t, and $Ask_{i,t,d}$ and $Bid_{i,t,d}$ are the closing ask and bid prices of the stock i on day d of year t.
- *-Ln(Turnover)* is defined as $-ln(\frac{1}{Days_{i,t}}\sum_{d=1}^{Days_{i,t}}\frac{Vol_{i,t,d}}{Shrout_{i,t,d}})$ where $Vol_{i,t,d}$ and $Shrout_{i,t,d}$ are the trading volume in shares and number of shares outstanding for firm i in day d of fiscal year t. (We use “negative” turnover so that it measures illiquidity.)
- *Ln(Analyst Dispersion)* is defined as $ln(1+100\times\frac{SD(AnalystForecast)}{|MedianForecastedEarnings|})$.
- *Ln(Analyst Error)* is defined as $ln(1+100\times\frac{|ActualEarnings-MedianForecastedEarnings|}{|ActualEarnings|})$.
- *Ln(Patent Grants)* is the logarithm of one plus the number of patent grants in the year.
- *Ln(Assets)* is the natural logarithm of total assets.
- *Leverage* is the sum of long term debt and debt in current liabilities divided by total assets.
- *Q* is the sum of total assets and the difference between market value and book value of total common equity, divided by total assets.
- *Profitability* is equal to EBITDA divided by total assets.
- *Cash* is the cash and equivalent divided by total assets.
- *Tangibility* is the net total value of property, plant and equipment, divided by total assets.

- *Ln(Age)* is the natural logarithm of firm age in years.
- *Return Volatility* is the standard deviation of daily stock returns in the fiscal year.
- *Ln(Number of Analysts)* is the natural logarithm of one plus maximum number of analysts following the stock for the year. It is coded as 0 if there is not coverage from I/B/E/S.
- *Market Share* is the fraction of sales the firm accounted for in the corresponding 4-digit SIC industry.
- *Dividend Dummy* is a binary variable that equals to 1 if firms pay dividend to common or preferred stockholders and 0 otherwise.
- *Public Debt Dummy* is a binary variable that equals to 1 if firms have available S&P credit rating and 0 otherwise.

APPENDIX C

VARIABLE DEFINITION FOR CHAPTER 3

- *Ln(Assets)* is the natural logarithm of total assets.
- *ROA* is equal to operating income divided by total assets.
- *Market-to-Book*: is the market value of equity plus total liability minus deferred taxes and investment tax credit, divided by total assets.
- *Net Worth Ratio*: is the shareholders' equity divided by total assets.
- *Current Ratio*: is total current assets divided by total assets.
- *Ln(R&D)* is the natural logarithm of R&D expenditure.
- *Ln(Patent)* is the natural logarithm of adjusted number of patent applications. The number is adjusted by dividing the number of patents for each firm-year by the mean number of patents of the same patent technology class and year.
- *Ln(Citations per Patent)* is the natural logarithm of adjusted number of citations per patent. The number is adjusted by dividing the number of citations for each firm-year by the mean number of citations of the same patent technology class and year.
- *Innovative Efficiency (Patent)* is the ratio of the number of patent applications of the year divided by the depreciated R&D stock of the past five years.
- *Innovative Efficiency (Citation)* is the ratio of the number of citations for the patents applied in the year divided by the depreciated R&D stock of the past five years.

REFERENCES

[1] Acharya, V. V., Baghai, R. P., and Subramanian, K. V., "Wrongful discharge laws and innovation," *Review of Financial Studies*, p. hht009, 2013.

[2] Acharya, V. V. and Subramanian, K. V., "Bankruptcy codes and innovation," *Review of Financial Studies*, p. hhp019, 2009.

[3] Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P., "Competition and innovation: an inverted-u relationship," *The Quarterly Journal of Economics*, vol. 120, pp. 701–728, May 2005.

[4] Aghion, P. and Bolton, P., "An incomplete contracts approach to financial contracting," *The Review of Economic Studies*, vol. 59, no. 3, pp. 473–494, 1992.

[5] Aghion, P., Van Reenen, J., and Zingales, L., "Innovation and institutional ownership," *American Economic Review*, vol. 103, pp. 277–304, Feb. 2013.

[6] Allen, F., "Stock markets and resource allocation," *Capital Markets and Financial Intermediation*, p. 81, 1995.

[7] Almeida, H., Hsu, P.-H., and Li, D., "Less is more: Financial constraints and innovative efficiency," working paper, May 2011.

[8] Amihud, Y., "Illiquidity and stock returns: Cross-section and time-series effects," *Journal of Financial Markets*, vol. 5, pp. 31–56, Jan. 2002.

[9] Amihud, Y. and Mendelson, H., "Asset pricing and the bid-ask spread," *Journal of Financial Economics*, vol. 17, pp. 223–249, Dec. 1986.

[10] Atanassov, J., "Do hostile takeovers stifle innovation? evidence from antitakeover legislation and corporate patenting," *The Journal of Finance*, vol. 68, no. 3, pp. 1097–1131, 2013.

[11] Atanassov, J., Nanda, V., and Seru, A., "Finance and innovation: The case of publicly traded firms," working paper, 2007.

[12] Baker, M., "Capital market-driven corporate finance," *Annual Review of Financial Economics*, vol. 1, no. 1, pp. 181–205, 2009.

[13] Baker, M., Stein, J. C., and Wurgler, J., "When does the market matter? stock prices and the investment of equity-dependent firms," *The Quarterly Journal of Economics*, vol. 118, pp. 969–1005, Aug. 2003.

[14] Bakke, T.-E. and Whited, T. M., "Which firms follow the market? an analysis of corporate investment decisions," *Review of Financial Studies*, p. hhp115, 2010.

[15] Balakrishnan, K., Billings, M., Kelly, B., and Ljungqvist, A., "Shaping liquidity: On the causal effects of voluntary disclosure," working paper, 2012.

[16] Baumol, W. J., *The Free-Market Innovation Machine: Analyzing the Growth Miracle of Capitalism.* Princeton university press, 2002.

[17] Bena, J. and Garlappi, L., "Corporate innovation and returns," working paper, 2012.

[18] Benfratello, L., Schiantarelli, F., and Sembenelli, A., "Banks and innovation: Microeconometric evidence on italian firms," *Journal of Financial Economics*, vol. 90, no. 2, pp. 197–217, 2008.

[19] Bond, P., Edmans, A., and Goldstein, I., "The real effects of financial markets," *Annual Review of Financial Economics*, vol. 4, no. 1, pp. 339–360, 2012.

[20] Branstetter, L. G., Fisman, R., and Foley, C. F., "Do stronger intellectual property rights increase international technology transfer? empirical evidence from u. s. firm-level panel data," *The Quarterly Journal of Economics*, vol. 121, pp. 321–349, Feb. 2006.

[21] Brown, J. R., Fazzari, S. M., and Petersen, B. C., "Financing innovation and growth: Cash flow, external equity, and the 1990s r&d boom," *The Journal of Finance*, vol. 64, no. 1, pp. 151–185, 2009.

[22] Bushee, B. J., "Investors on myopic r&d investment behavior," *The Accounting Review*, vol. 73, no. 3, pp. 305–333, 1998.

[23] Butler, A. W., Grullon, G., and Weston, J. P., "Stock market liquidity and the cost of issuing equity," *The Journal of Financial and Quantitative Analysis*, vol. 40, pp. 331–348, June 2005.

[24] Cai, J., Cremers, K. J. M., and Wei, K., "CEO compensation and stock mispricing: How do boards react to mutual fund flow-driven price pressure?," working paper, Nov. 2012.

[25] Carey, M. and Hrycray, M., "Credit flow, risk, and the role of private debt in capital structure," *Unpublished working paper, Federal Reserve Board*, 1999.

[26] Chava, S. and Roberts, M. R., "How does financing impact investment? the role of debt covenants," *The Journal of Finance*, vol. 63, no. 5, pp. 2085–2121, 2008.

[27] Chava, S., Nanda, V., and Xiao, S. C., "Lending to innovative firms," working paper, 2013.

[28] Chava, S., Oettl, A., Subramanian, A., and Subramanian, K. V., "Banking deregulation and innovation," *Journal of Financial Economics*, vol. 109, pp. 759–774, Sept. 2013.

[29] Chen, Q., Goldstein, I., and Jiang, W., "Price informativeness and investment sensitivity to stock price," *Review of Financial Studies*, vol. 20, pp. 619–650, May 2007.

[30] Cohen, L., Diether, K., and Malloy, C., "Misvaluing innovation," *Review of Financial Studies, forthcoming*, 2012.

[31] Cohen, W. M., Nelson, R. R., and Walsh, J. P., "Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not)," working paper, National Bureau of Economic Research, 2000.

[32] Coval, J. and Stafford, E., "Asset fire sales (and purchases) in equity markets," *Journal of Financial Economics*, vol. 86, pp. 479–512, Nov. 2007.

[33] Dass, N., Nanda, V., and Xiao, S. C., "Innovative firms and the endogenous choice of stock liquidity," working paper, Apr. 2013.

[34] Dewatripont, M. and Tirole, J., "A theory of debt and equity: Diversity of securities and manager-shareholder congruence," *The Quarterly Journal of Economics*, vol. 109, no. 4, pp. 1027–1054, 1994.

[35] Dichev, I. D. and Skinner, D. J., "Largesample evidence on the debt covenant hypothesis," *Journal of Accounting Research*, vol. 40, no. 4, pp. 1091–1123, 2002.

[36] Dong, M., Hirshleifer, D., Richardson, S., and Teoh, S. H., "Does investor misvaluation drive the takeover market?," *The Journal of Finance*, vol. 61, no. 2, pp. 725–762, 2006.

[37] Dong, M., Hirshleifer, D., and Teoh, S. H., "Overvalued equity and financing decisions," *Review of Financial Studies*, vol. 25, pp. 3645–3683, Dec. 2012.

[38] Dow, J. and Gorton, G., "Stock market efficiency and economic efficiency: is there a connection?," *The Journal of Finance*, vol. 52, no. 3, pp. 1087–1129, 1997.

[39] Duarte, J. and Young, L., "Why is PIN priced?," *Journal of Financial Economics*, vol. 91, pp. 119–138, Feb. 2009.

[40] Durnev, A., Morck, R., and Yeung, B., "Value-enhancing capital budgeting and firm-specific stock return variation," *The Journal of Finance*, vol. 59, no. 1, pp. 65–105, 2004.

[41] Easley, D., Hvidkjaer, S., and OHara, M., "Is information risk a determinant of asset returns?," *The Journal of Finance*, vol. 57, no. 5, pp. 2185–2221, 2002.

[42] Easley, D. and O'Hara, M., "Microstructure and asset pricing," in *Handbook of the Economics of Finance* (G.M. Constantinides, M. H. a. R. S., ed.), vol. Volume 1, Part B, pp. 1021–1051, Elsevier, 2003.

[43] Edmans, A., "Blockholder trading, market efficiency, and managerial myopia," *The Journal of Finance*, vol. 64, no. 6, pp. 2481–2513, 2009.

[44] Edmans, A., Gabaix, X., and Landier, A., "A multiplicative model of optimal CEO incentives in market equilibrium," *Review of Financial Studies*, vol. 22, pp. 4881–4917, Dec. 2009.

[45] Edmans, A., Goldstein, I., and Jiang, W., "The real effects of financial markets: The impact of prices on takeovers," *The Journal of Finance*, vol. 67, no. 3, pp. 933–971, 2012.

[46] Falato, A. and Liang, N., "Do creditor rights increase employment risk? evidence from debt covenants," working paper, Federal Reserve Board, 2008.

[47] Falvey, R., Foster, N., and Greenaway, D., "Intellectual property rights and economic growth," *Review of Development Economics*, vol. 10, no. 4, pp. 700–719, 2006.

[48] Fang, V. W., Noe, T. H., and Tice, S., "Stock market liquidity and firm value," *Journal of Financial Economics*, vol. 94, no. 1, pp. 150–169, 2009.

[49] Foucault, T. and Fresard, L., "Learning from peers' stock prices and corporate investment," *Journal of Financial Economics*, vol. 111, no. 3, pp. 554–577, 2014.

[50] Foucault, T. and Frsard, L., "Cross-listing, investment sensitivity to stock price, and the learning hypothesis," *Review of Financial Studies*, vol. 25, no. 11, pp. 3305–3350, 2012.

[51] Foucault, T. and Gehrig, T., "Stock price informativeness, cross-listings, and investment decisions," *Journal of Financial Economics*, vol. 88, no. 1, pp. 146–168, 2008.

[52] Friedman, D. D., Landes, W. M., and Posner, R. A., "Some economics of trade secret law," *The Journal of Economic Perspectives*, pp. 61–72, 1991.

[53] Gallini, N. T., "The economics of patents: Lessons from recent u.s. patent reform," *The Journal of Economic Perspectives*, vol. 16, pp. 131–154, Apr. 2002.

[54] Gao, P. and Lou, D., "Cross-market timing in security issuance," working paper, 2012.

[55] Glass, A. J. and Saggi, K., "Intellectual property rights and foreign direct investment," *Journal of International Economics*, vol. 56, pp. 387–410, Mar. 2002.

[56] Gould, D. M. and Gruben, W. C., "The role of intellectual property rights in economic growth," *Journal of Development Economics*, vol. 48, pp. 323–350, Mar. 1996.

[57] Graham, J. R., Harvey, C. R., and Rajgopal, S., "The economic implications of corporate financial reporting," *Journal of Accounting and Economics*, vol. 40, no. 1, pp. 3–73, 2005.

[58] Graham, S. and Sichelman, T., "Patenting by entrepreneurs: an empirical study," *Michigan Telecommunications and Technology Law Review*, vol. 17, pp. 111–180, 2010.

[59] Graham, S. J. and Sichelman, T., "Why do start-ups patent," *Berkeley Tech. LJ*, vol. 23, p. 1063, 2008.

[60] Grossman, S., "On the efficiency of competitive stock markets where trades have diverse information," *The Journal of Finance*, vol. 31, no. 2, pp. 573–585, 1976.

[61] Grullon, G., Michenaud, S., and Weston, J. P., "The real effects of short-selling constraints," working paper, 2012.

[62] Gu, Y., Mao, C. X., and Tian, X., "Bank interventions and firm innovation: Evidence from debt covenant violations," working paper, Sept. 2014.

[63] Hadlock, C. J. and Pierce, J. R., "New evidence on measuring financial constraints: Moving beyond the KZ index," *Review of Financial Studies*, vol. 23, pp. 1909–1940, May 2010.

[64] Hall, B. H., Jaffe, A. B., and Trajtenberg, M., "The NBER patent citation data file: Lessons, insights and methodological tools," working paper, National Bureau of Economic Research, 2001.

[65] Hall, B. H. and Lerner, J., "The financing of r&d and innovation," working paper, National Bureau of Economic Research, Sept. 2009.

[66] Hall, B. H. and Ziedonis, R. H., "The patent paradox revisited: an empirical study of patenting in the US semiconductor industry, 1979-1995," *RAND Journal of Economics*, pp. 101–128, 2001.

[67] Hau, H. and Lai, S., "Real effects of stock underpricing," *Journal of Financial Economics*, vol. 108, pp. 392–408, May 2013.

[68] Hellwig, M. F., "On the aggregation of information in competitive markets," *Journal of Economic Theory*, vol. 22, no. 3, pp. 477–498, 1980.

[69] Himmelberg, C. P. and Petersen, B. C., "R & d and internal finance: A panel study of small firms in high-tech industries," *The Review of Economics and Statistics*, pp. 38–51, 1994.

[70] Hirshleifer, D., Hsu, P.-H., and Li, D., "Innovative efficiency and stock returns," *Journal of Financial Economics*, vol. 107, pp. 632–654, Mar. 2013.

[71] Hoberg, G. and Phillips, G., "Product market synergies and competition in mergers and acquisitions: A text-based analysis," *Review of Financial Studies*, vol. 23, no. 10, pp. 3773–3811, 2010.

[72] Hoberg, G. and Phillips, G. M., "Text-based network industries and endogenous product di fferentiation," working paper, National Bureau of Economic Research, 2010.

[73] Holmstrm, B., "Moral hazard and observability," *The Bell Journal of Economics*, pp. 74–91, 1979.

[74] Holmstrm, B., "Agency costs and innovation," *Journal of Economic Behavior & Organization*, vol. 12, no. 3, pp. 305–327, 1989.

[75] Holmstrm, B. and Tirole, J., "Market liquidity and performance monitoring," *Journal of Political Economy*, vol. 101, pp. 678–709, Aug. 1993.

[76] Houston, J. and James, C., "Bank information monopolies and the mix of private and public debt claims," *The Journal of Finance*, vol. 51, no. 5, pp. 1863–1889, 1996.

[77] Hsu, D. H. and Ziedonis, R. H., "Patents as quality signals for entrepreneurial ventures.," *Academy of Management Proceedings*, vol. 2008, pp. 1–6, Aug. 2008.

[78] Imbens, G. and Kalyanaraman, K., "Optimal bandwidth choice for the regression discontinuity estimator," *The Review of Economic Studies*, vol. 79, no. 3, pp. 933–959, 2012.

[79] Jaffe, A. B., "The u.s. patent system in transition: policy innovation and the innovation process," *Research Policy*, vol. 29, pp. 531–557, Apr. 2000.

[80] Jensen, M. C., "Agency costs of free cash flow, corporate finance, and takeovers," *The American Economic Review*, pp. 323–329, 1986.

[81] Jensen, M. C. and Meckling, W. H., "Theory of the firm: Managerial behavior, agency costs and ownership structure," *Journal of Financial Economics*, vol. 3, pp. 305–360, Oct. 1976.

[82] Johnson, S. A., "An empirical analysis of the determinants of corporate debt ownership structure," *Journal of Financial and Quantitative Analysis*, vol. 32, no. 01, pp. 47–69, 1997.

[83] Kau, J. B., Linck, J. S., and Rubin, P. H., "Do managers listen to the market?," *Journal of Corporate Finance*, vol. 14, pp. 347–362, Sept. 2008.

[84] Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N., "Technological innovation, resource allocation, and growth," Working Paper 17769, National Bureau of Economic Research, Jan. 2012.

[85] Kortum, S. and Lerner, J., "Assessing the contribution of venture capital to innovation," *RAND Journal of Economics*, pp. 674–692, 2000.

[86] Lai, R., DAmour, A., Yu, A., Sun, Y., Torvik, V., and Fleming, L., "Disambiguation and co-authorship networks of the US patent inventor database," *Harvard Institute for Quantitative Social Science, Cambridge, MA*, vol. 2138, 2011.

[87] Lanjouw, J. and Schankerman, M., "Protecting intellectual property rights: Are small firms handicapped?," *Journal of Law and Economics*, vol. 47, pp. 45–74, Apr. 2004.

[88] Lee, J.-Y. and Mansfield, E., "Intellectual property protection and u.s. foreign direct investment," *The Review of Economics and Statistics*, vol. 78, pp. 181–186, May 1996.

[89] Leland, H. E. and Pyle, D. H., "Informational asymmetries, financial structure, and financial intermediation," *The Journal of Finance*, vol. 32, no. 2, pp. 371–387, 1977.

[90] Lerner, J., "Patenting in the shadow of competitors," *Journal of Law and Economics*, pp. 463–495, 1995.

[91] Lerner, J., "Using litigation to understand trade secrets: A preliminary exploration," Working Paper ID 922520, Aug. 2006.

[92] Lerner, J., "The empirical impact of intellectual property rights on innovation: Puzzles and clues," *The American Economic Review*, vol. 99, pp. 343–348, May 2009.

[93] Lerner, J., Sorensen, M., and Strmberg, P., "Private equity and long-run investment: The case of innovation," *The Journal of Finance*, vol. 66, no. 2, pp. 445–477, 2011.

[94] Luo, Y., "Do insiders learn from outsiders? evidence from mergers and acquisitions," *The Journal of Finance*, vol. 60, no. 4, pp. 1951–1982, 2005.

[95] Mann, R., "Do patents facilitate financing in the software industry," *Texas Law Review*, vol. 83, no. 4, pp. 962–1030, 2006.

[96] Mansfield, E., "Patents and innovation: an empirical study," *Management science*, vol. 32, no. 2, pp. 173–181, 1986.

[97] MASKUS, K. E. and PENUBARTI, M., "How trade-related are intellectual property rights?," *Journal of International Economics*, vol. 39, pp. 227–248, Nov. 1995.

[98] NANDA, R. and NICHOLAS, T., "Did bank distress stifle innovation during the great depression?," working paper, 2012.

[99] NANDA, V., DASS, N., and XIAO, S. C., "Truncation bias in patent data," working paper, 2014.

[100] NINI, G., SMITH, D. C., and SUFI, A., "Creditor control rights and firm investment policy," *Journal of Financial Economics*, vol. 92, no. 3, pp. 400–420, 2009.

[101] NINI, G., SMITH, D. C., and SUFI, A., "Creditor control rights, corporate governance, and firm value," *Review of Financial Studies*, vol. 25, no. 6, pp. 1713–1761, 2012.

[102] OZOGUZ, A. and REBELLO, M., "Information, competition, and investment sensitivity to peer stock prices," *Competition, and Investment Sensitivity to Peer Stock Prices (July 2, 2013)*, 2013.

[103] PAGANO, M., RELL, A. A., and ZECHNER, J., "The geography of equity listing: Why do companies list abroad?," *The Journal of Finance*, vol. 57, no. 6, pp. 2651–2694, 2002.

[104] PARK, W. G. and GINARTE, J. C., "Inlectual property rights and economic growth," *Contemporary Economic Policy*, vol. 15, no. 3, pp. 51–61, 1997.

[105] PETERSEN, M. A., "Estimating standard errors in finance panel data sets: Comparing approaches," *Review of Financial Studies*, vol. 22, no. 1, pp. 435–480, 2009.

[106] PNG, I., "Law and innovation: evidence from state trade secrets laws," working paper, 2014.

[107] POLK, C. and SAPIENZA, P., "The stock market and corporate investment: A test of catering theory," *Review of Financial Studies*, vol. 22, pp. 187–217, Jan. 2009.

[108] RAJAN, R. and ZINGALES, L., "Banks and markets: The changing character of european finance," working paper, 2003.

[109] ROBERTS, M. and WHITED, T., "Endogeneity in empirical corporate finance," in *Handbook of the Economics of Finance*, vol. 2, 2010.

[110] ROMER, P. M., "Endogenous technological change," *Journal of Political Economy*, pp. S71–S102, 1990.

[111] Scherer, F. M., *Patens and Corporation.* James J. Galvin, 1959.

[112] Seru, A., “Firm boundaries matter: Evidence from conglomerates and r&d activity,” *Journal of Financial Economics*, vol. 111, pp. 381–405, Feb. 2014.

[113] Shleifer, A. and Summers, L. H., “Breach of trust in hostile takeovers,” in *Corporate takeovers: Causes and consequences*, pp. 33–68, University of Chicago Press, 1988.

[114] Silverman, B. W., *Density estimation for statistics and data analysis*, vol. 26. CRC press, 1986.

[115] Smith, C. W. and Warner, J. B., “On financial contracting: An analysis of bond covenants,” *Journal of Financial Economics*, vol. 7, no. 2, pp. 117–161, 1979.

[116] Solow, R. M., “Technical change and the aggregate production function,” *The Review of Economics and Statistics*, vol. 39, pp. 312–320, Aug. 1957.

[117] Stein, J. C., “Takeover threats and managerial myopia,” *Journal of Political Economy*, vol. 96, pp. 61–80, Feb. 1988.

[118] Stein, J. C., “Rational capital budgeting in an irrational world,” *The Journal of Business*, vol. 69, pp. 429–455, Oct. 1996.

[119] Sweeney, A. P., “Debt-covenant violations and managers’ accounting responses,” *Journal of Accounting and Economics*, vol. 17, no. 3, pp. 281–308, 1994.

[120] Taylor, C. T., Silberston, A., and Silberston, Z. A., *The economic impact of the patent system: a study of the British experience*, vol. 23. CUP Archive, 1973.

[121] Taylor, M. S., “Trips, trade, and growth,” *International Economic Review*, vol. 35, no. 2, pp. 361–381, 1994.

[122] Tian, X. and Wang, T., “Tolerance for failure and corporate innovation,” *Review of Financial Studies, forthcoming*, 2011.

[123] Whited, T. M. and Wu, G., “Financial constraints risk,” *Review of Financial Studies*, vol. 19, pp. 531–559, June 2006.

[124] Zhao, M., “Conducting r&d in countries with weak intellectual property rights protection,” *Management Science*, vol. 52, pp. 1185–1199, Aug. 2006.

[125] Ziedonis, R., “Intellectual property and innovation,” in *The Handbook of Technology and Innovation Management*, 2008.

VITA

Steven Chong Xiao is currently an Assistant Professor of Finance at Rutgers Business School. Prior to studying for his Ph.D. in Finance at Georgia Tech, he has a Bachelor's degree in Finance from the Hong Kong University of Science and Technology and a Master's degree in Quantitative and Computational Finance at Georgia Tech. His research interests are in empirical corporate finance and international finance. His paper "Culture and R^2" with Cheol S. Eun and Lingling Wang is forthcoming in the *Journal of Financial Economics*. His papers have been presented at various finance conferences such as the European Finance Association, the Northern Finance Association, the Society for Financial Econometrics, and Kauffman Entrepreneurial Finance and Innovation Conference.