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Essays in corporate finance

Yiwei YU
Singapore Management University

ESSAYS IN CORPORATE FINANCE

YU YIWEI

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By
Yu Yiwei

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Dissertation Committee:

Jerry Cao Xiaping (Supervisor/Chair)
Assistant Professor of Finance
Singapore Management University

Jeremy Goh
Associate Professor of Finance
Singapore Management University

Aurobindo Ghosh
Assistant Professor of Finance
Singapore Management University

Yongheng Deng
Professor of Real Estate and Finance
National University of Singapore

Singapore Management University
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YU Yiwei

Abstract

Innovation is vital to companies’ competitive advantages and is an important driver of economic growth. However, innovation is costly, since the innovation process is long, idiosyncratic, and uncertain, often involving a very high failure probability and great positive externalities .We thus launch the investigation from the following three aspects to explore how to create a better environment for producing innovation: Financing of innovation; dual-class share structure of innovation; and regulation and policy (e.g. SOX Act.)'s impact on innovation.

First of all, we study the effect of firms’ real estate collateral on innovation. In the presence of financing frictions, firms can use real estate assets as collateral to finance innovation. Through this collateral channel, positive shocks to the value of real estate collateral enhance firms’ financing capacity and lead to more innovation. Empirically, a one standard deviation increase in a firm’s real estate valuation is associated with an 8% increase in the quantity, quality, generality, and originality of its patents applied in the same year, and such positive effect is persistent over subsequent five years. The positive effect is more pronounced for firms that are financially constrained, dependent on debt finance, or belonging to hard-to-innovate industries. Our results suggest that corporate real estate collateral serves an important role in mitigating financial constraints, which leads to more innovation outputs.

Second, we try to explore how the dual-class share structure would affect the in production of innovation. Despite the risk of power abuse by corporate insiders with excessive control rights, technology companies are increasingly adopting dual-class share structures. In this paper, we show that such structures are negatively associated with corporate innovation measures. For dual-class firms, patents are increasing in Tobin's Q, high-tech or hard-to-innovate industries, external takeover market threats or product market competition. Our findings are robust to reverse causality. To ensure that these findings are not the result of reverse causality, we examine a subsample of firms that switch from single-class

Third, we investigate whether innovation by publicly listed U.S. companies deteriorated significantly after the adoption of the Sarbanes-Oxley Act of 2002. Using data on patent filings as proxies for firms' innovative activities, we find firms' innovation as measured by patents and innovation efficiency dampened significantly after the enactment of the Act. The degree of impact is related to firm specific characteristics such as firm value (Tobin's Q) or corporate governance (G-Index) as well as firms' operating conditions (i.e., high-tech industries, delisted or not). We find evidence that SOX's impact on firms is more pronounced for growth firms, firms with low governance scores, firms operating in high-tech industries or firms that continued to stay listed. Overall, the results suggests that the SOX has an unintended consequence of stifling corporate innovation.

Keywords: Innovation; patents; Financing capacity; Real estate collateral; Financing constraints; dual-class; market conditions; corporate governance; Innovation; Sarbanes-Oxley; R&D expenditures

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Part I Corporate Real Estate Collateral and Innovation

Chapter 1 Introduction

Innovation is vital to companies' competitive advantages (Porter, 1992) and is an important driver of economic growth (Solow, 1957; Baumol, 2001). However, innovation is costly, since the innovation process is long, idiosyncratic, and uncertain, often involving a very high failure probability (Holmstrom, 1989) and great positive externalities (Arrow, 1962). As a result, under-investment in innovation is prevalent. Hall and Lerner (2010) attribute such under-investment to a severe "funding gap".

A large literature suggests that a firm's debt financing capacity, i.e., ability to access debt financing at low cost and respond to changes in investment opportunities in a timely manner (Denis, 2011), affects its investment policy. Corporations rely heavily on bank loans and corporate debts as their sources of external financing, the use of collateral is important as it helps alleviate agency costs in the presence of moral hazard, adverse selection, or contracting frictions due to asymmetric information (Chan and Thakor, 1987; Mayer, 1990; Holmstrom and Tirole, 1997; Berger, Espinosa-Vega, Frame, and Miller, 2011). For example, Benmelech, Garmaise, and Moskowitz (2005) show that the liquidation values of collateralized assets are first-order determinants of loan contract terms. Firms with greater collateral value are able to raise external funds at lower cost (e.g. Berger, Frame and Ioannidou, 2011; Lin, Ma, Malatesta, and Xuan, 2011). Thus, a large decline in the value of collateralized assets reduces a firm's credit-worthiness, which negatively impacts its debt financing capacity and ability to invest (e.g., Bernanke and Gertler, 1989, 1990), while a positive shock to collateralized assets enhances a firm's debt financing capacity, which allows it to borrow and invest more (Barro, 1976; Stiglitz and Weiss, 1981; Hart and Moore, 1994; Tirole, 2005; Jimenez, Salas and Saurina, 2006; Benmelech and Bergman, 2009).

Notwithstanding the extensive evidence on the link between debt financing capacity and investment (see Hubbard (1998) and Stein (2003) for comprehensive reviews), to the best of our knowledge no prior study directly tests the role of debt financing capacity on investment in innovation. In this paper we address this gap in the literature by building on recent studies on the role of collateral in mitigating financing constraints. This literature establishes that a firm's real assets collateral can be used to reduce financing costs, enhance financing capacity, and mitigate financing constraints. We hypothesize that, to the extent that firms' innovation decisions are affected by their financing capacity, the improvement in firms' financing capacity due to increases in the collateralized real estate value should enhance their innovation output.

An empirical challenge in making causal inferences between debt financing capacity and innovation lies in identifying an exogenous shock to these variables. For instance, a firm's innovation policy might have feedback effects on the firm's financing capacity. Unobservable firm heterogeneity correlated with both financing capacity and innovation policies could also bias empirical results. To empirically test our hypothesis, we exploit changes in the real estate prices at the Metropolitan Statistical Area (MSA) or state level as exogenous shocks to the collateral value of a firm's real estate assets. Prior work shows that the value of the real estate that a firm owns will affect its financing capacity through the collateral channel, particularly for financing-constrained firms (e.g., Gan, 2007; Benmelech and Bergman, 2009; Chaney, Sraer, and Thesmar, 2012). Thus, if financing capacity affects a firm's investment in innovation, we would expect an exogenous positive (negative) shock to the value of collateralized real estate to result in increased (decreased) corporate innovation productivity. A key advantage of this identification strategy is that it not only captures variation in exogenous shocks to debt financing capacity, but also solves the omitted variables concern by allowing for multiple shocks to different firms at different times and locations. Turning to innovation, we follow prior literature (e.g., Lerner, Sorensen and Stromberg, 2011) and use the number of patent applications in a given year that are eventually granted as the innovation measure. Patents are valuable innovation outputs that are actively traded in intellectual property markets. The number of patent applications eventually granted is thus a direct measure of the quantity and quality of a firm's innovation activity (Griliches, 1990). In additional analyses, we also use the number of patent citations, patent generality, and patent originality as alternative measures of innovation productivity.

Using a comprehensive sample of U.S. firms from COMPUSTAT Data over the 1993 to 2006 period, we find that a change in corporate real estate collateral value is significantly positively associated with innovation productivity. In particular, a one-standard-deviation increase in the logarithm of the value of collateralized real estate assets in year *t* is associated with an 8.2% increase in the number of patent applications, or 0.33 new patent applications, in the same year for a given firm. The positive effect of a change in the value of real estate assets on innovation is even stronger in year *t*+1, and then decreases gradually but remains significant through yeart+5. We observe similarly strong and significant positive effects of real estate collateral on our alternative measures of innovation productivity, namely, the number of patent citations as well as patent generality and originality.

The analysis above may subject to endogeneity concerns. First, real estate prices could be correlated with local innovation performance. For example, Firms that are more productive in innovation may demand for more local labor and local products, thus they could push up real estate prices in the local market, which would be captured by the increase in their own real estate assets value. We address this concern using two-stage instrumental variable (IV) regressions. Following Himmelberg, Mayer, and Sinai (2005), Mian and Sufi (2011), and Chaney, Sraer, and Thesmar (2012), we use the interaction of local housing supply elasticity and long-term real interest rate as an instrument. These two variables are not related to corporate innovation productivity but are highly associated with the real state price. The IV regressions report robust positive relationship between the change in real estate value and innovation productivity, suggesting that our findings are not driven by reverse causality problems.

Second, a firm with more innovation may decide to own more real estate assets, leading to an increase in the value of its real estate assets. We make two attempts address the second concern: (1) we control for observable determinants of firms' real estate ownership decision in our baseline regressions. The results remain unchanged; (2) we run subsample regressions examining the sensitivity of innovation on real estate prices for the non-land-purchasers that never own real estate, the future purchases before they do so, and the purchases after they do so, separately. We find that the sensitivity is large, positive, and significant only after firms acquire real estate. However, the sensitivity is statistically insignificant for the purchasers before they acquire real estate and the non-land-purchasers that never own real estate. Thus our findings are not driven by omitted firm characteristics affecting the real estate ownership decision and innovation.

After demonstrating that the collateral value of real estate has a positive effect on innovation outputs, we then partition our sample in several ways to examine the possible mechanisms explaining the positive effect. First, we test whether companies' financial constraints affect the sensitivity of their innovation outputs respond to changes in the value of real estate collateral. In the presence of financial constraints, constrained firms can use their real estate assets as collateral to finance their investment in innovation when they otherwise would be unable to do so. We hence expect such positive effects of real estate collateral to be stronger for constrained firms with costly and limited debt financing sources. Our findings are consistent with this prediction. Utilizing measures like the KZ index, debt rating and paper rating as proxies for financial constraints (Kaplan and Zingales, 1997; Whited and Wu, 2006; Denis and Sibilkov, 2010; Farre-Mensa and Ljungqvist, 2013), we find that the positive effect concentrates in the subsample of financially constrained firms and is insignificant for firms not subjecting to financial constraints. Our findings thus demonstrate that companies with costly and limited financial resources benefit the most from the appreciation of real estate collateral value to improve their innovation.

Second, we test how debt financing dependence impacts the positive effect of real estate collateral on innovation. As the collateral value of real estate assets appreciates, financially constrained firm can borrow external debt as a fraction the collateral value of their real estate assets. The literature (e.g., in Hart and Moore 1994; Chaney, Sraer, and Thesmar, 2012) shows that an increase in collateral value indeed leads to more issues of debt secured on the appreciated value of land holdings, which provides financing for investment in innovation. We thus expect that the positive effect of real estate collateral on innovation would be stronger for debt dependent firms which have relatively greater need for debt financing compared to firms that only reply on equity financing. Empirically, we find that an increase in the value of real estate collateral leads to significantly more innovation for firms with existing debt outstanding, as a proxy for debt financing dependence, and no impact for firms without debt. Again, our findings provide evidence that companies that have greater needs for debt financing take advantage of the appreciation of real estate collateral value to improve their innovation.

Lastly, if an increase in the collateral value of real estate assets improves firms' innovation, because it helps to mitigate financial constraint and enhance debt financing capacity through alleviating agency costs and contracting frictions associated with the innovation process which is long, uncertain, often involving a very high failure probability. We expect that the positive effect of real estate collateral should be especially pronounced in hard to innovation industries where the innovation process is highly long, uncertain, involving high failure risk, and demanding large resources. We split the full sample into two subsamples according to whether or not firms belong to difficult to innovation industries, following the work of Hall, Jaffe, and Trajtenberg (2005) and Tian and Wang (2011) based on patent technology class. We find that the positive effect of real estate collateral only exists in the subsample of difficult to innovation industries and is insignificant for easy to innovation industries. These results hence suggest that the positive effect of real estate collateral for innovation is greater in industries in which innovation is more difficult to achieve, consistent with our prediction.

Our research contributes to the literature on the relationship between innovation and financing. Cornaggia, Mao, Tian, and Wolfe (2013) show that banks provide an important source of external financing for corporate innovation, particularly for firms that are financially constrained. Hsu, Tian and Xu (2013) instead show that the development of financial markets, especially equity markets, is important in encouraging innovation. Similarly, Atanassov, Nanda, and Seru (2007) find that publicly traded firms tend to rely on arm's length equity financing rather than relationship-based bank financing to invest in innovation. While the question of whether equity or debt financing is more relevant in stimulating innovation is outside the scope of the current paper, we shed light on the debate by showing empirically that the increase in debt financing capacity associated with an increase in the value of firms’ real estate collateral leads to greater innovation.

The remainder of the paper is organized as follows. In Section 2 we discuss our sample, the variables used in the analysis, and summary statistics. In Section 3 we present the empirical results of baseline regressions and robustness tests, and in Section 4 we conclude.

Chapter 2 Sample Selection, Variable Measurement, and Summary Statistics

1.2.1 Sample Selection

Our sample construction and empirical approach follow Chaney, Sraer, and Thesmar (2012), who identify variations in local real estate prices, either at the state of the MSA level, as exogenous shocks to firms' financing capacity through the collateral channel. To obtain the market value of firms' real estate holdings, we start with the sample of firms on COMPUSTAT in 1993 with non-missing total assets. We require that the firms exist in 1993 as this was the last year for which data on accumulated depreciation on buildings are available in COMPUSTAT. We next require that sample firms have sufficient information available to calculate the market value of real estate assets. We then omit firms not headquartered in the U.S., as well as firms not present for at least three consecutive years in the sample. We further exclude firms belonging to the finance, insurance, real estate, construction, or mining industries, and firms involved in major acquisitions. These filters result in a sample of 26,083 U.S. firm-year observations over the period 1993 to 2006.

For each sample firm we collect annual information on innovation activity from the National Bureau of Economic Research (NBER) Patent Citation Data File. This dataset contains detailed information on more than three million patents granted by the United States Patent and Trademark Office (USPTO) from 1976 to 2006. It provides information such as patent assignee names, number of patents, number of citations received by each patent, patent application year as well as grant year, and patent technology class. One advantage of the NBER database is that it is unlikely to be affected by survivorship bias. As long as a patent application is eventually granted by the USPTO, it is attributed to the applying firm at the time of application even if the firm later gets acquired or goes bankrupt. Moreover, because patent citations are attributed to a patent and not the applying firm, the patent granted to a firm that later gets acquired or goes bankrupt can still receive citations long after the firm disappears.

We merge the NBER patent data with the real estate data from COMPUSTAT using a bridge file provided by the NBER database in which GVKEY is the common identifier. Following the innovation literature, we set the number of patents and citations to zero for firms that have no patent information available in the NBER database.

1.2.2 Variable Measurement

1.2.2.1 Real Estate Value

To measure the market value of a firm's real estate collateral, we first follow Nelson, Potter, and Wilde (2000) to define a firm's real estate assets as the sum of the three major categories of property, plant, and equipment (PPE): PPE land and improvement at cost (FATP in COMPUSTAT), PPE buildings at cost (FATB in COMPUSTAT), and PPE construction-in-progress at cost (FATC in COMPUSTAT). Then, because these assets are valued at historical cost rather than marked-to-market, we follow Chaney, Sraer, and Thesmar (2012) to recover their market value by calculating the average age of the assets and estimating their current market value using market prices.

The detailed steps to recover the market value of a firm's real estate assets are as follows. First, we take the ratio of the accumulated depreciation of buildings (DPACB in COMPUSTAT) to the historic cost of buildings (FATB in COMPUSTAT) and multiply by the assumed mean depreciable life of 40 years

(Nelson, Potter, and Wilde, 2000).[1] This calculation approximates the age or the acquisition year of the firm's real estate assets.

Second, to adjust real estate prices, we retrieve the MSA- or state-level real estate price index from the Office of Federal Housing Enterprise Oversight (OFHEO) for the period starting in 1975, when OFHEO real estate price index data are available, and the consumer price index (CPI) for the period prior to 1975. Because we have the mapping table between zip codes and MSA codes maintained by the U.S. Department of Labor's Office of Workers' Compensation Programs (OWCP) as well as the zip codes for each firm from COMPUSTAT, we use the zip code as an identifier to match the MSA code and the MSA-level real estate price index with accounting data for each firm from COMPUSTAT. Finally, we estimate the market value of a firm's real estate assets for each year in the sample period (1993 to 2004) by multiplying the book value of the assets at acquisition (FATP+FATB+FATC) by the real estate price index for the given year.

Note that following Chaney, Sraer, and Thesmar (2012), we do not incorporate the value of any real estate acquisitions or dispositions following 1993. This procedure helps to mitigate the possible endogeneity concern between real estate holdings and investment opportunities, since any future variations in the value of real estate assets are driven only by variations in real estate prices instead of endogenous changes in real estate holdings. In addition, as illustrated in Chaney et al. (2012), firms are not likely to sell real estate assets to realize the capital gains when confronted with an increase in their real estate value, thus alleviating some of our concerns stemming from measurement error on the real estate value.

[1] The accumulated depreciation on buildings (DPACB) is not reported in COMPUSTAT after 1993. This is why we restrict our sample to firms active in 1993 when measuring the market value of real estate assets.

In Appendix B, we illustrate the above approach using the case of General Motors (GM). In 1993, GM has accumulated depreciation of buildings of 6889.7 million U.S. dollars and historic cost of buildings of 13577 million U.S. dollars, and thus the ratio between these two items is 0.5075. To calculate the average age of GM's real estate assets as of 1993, we multiply 0.5075 by the assumed mean depreciable life of 40 years. This gives an average age of 20 years, which implies an average acquisition year of 1973. We next multiply the historical cost of GM's real estate assets by the cumulative price increase in the MSA-level real estate price index from 1973 to 1993 to obtain the market value of GM's real estate assets in 1993 (18278 million U.S. dollars). Finally, we adjust the market value of real estate assets by lagged PPE to obtain our final measure, *RE Value*, which is 126% in 1993. To estimate the market value of GM's real estate assets in subsequent years, we simply multiply the *RE Value* in 1993 by the cumulative price increase from 1993 to the year of interest.

We note that it is crucial in our analysis to control for the potential endogeneity concerns in our identification strategy: (1) the real estate prices may be correlated with innovation productivity; (2) the decision to own or lease real estate may be correlated with firms' innovation productivity. We address these concerns in Section 3.2 of our empirical analysis.

1.2.2.2 Innovation Productivity

Following recent innovation literature such as Seru (2012) for publicly traded firms and Lerner, Sorensen, and Stromberg (2011) for privately held firms, we capture a firm's innovation productivity using its patent activity, which indicates how effectively the firm transforms innovation inputs into outputs. More specifically, based on the information available in the NBER database, we construct four measures of a firm's patent activity.

Our first measure is the number of patent applications filed in a given year that are eventually granted. The number of patent applications can be thought of as capturing the *quantity* of innovation output. We use the patent's application year instead of grant year because Griliches, Pakes, and Hall (1988) argue that a patent's application year better matches the time of innovation than the patent's grant year. However, because patents appear in the NBER database only after they are granted, and it takes about two years on average for a successful patent application to be granted by the USPTO, many patent applications filed toward the end of our sample period (i.e., during 2005 and 2006) were still under review and had not been granted by 2006. We therefore limit patent application data to the 1993 to 2004 period to account for the truncation bias in patent application counts arising from the application-grant lag.

Our second measure of patent activity is motivated by the fact that, despite their straightforward interpretation and easy implementation, patent counts do not distinguish ground-breaking inventions from incremental technological discoveries. To further assess a firm's innovation productivity, we follow Hall, Jaffe, and Trajtenberg (2001, 2005) and examine the number of patent citations that a patent received. The number of patent citations can be thought of as capturing the *quality* of innovation output. To more precisely capture the impact of patents we exclude self-citations when computing the number of citations, but our results continue to hold when we include self-citations. Notice, however, that while a patent can receive citations over a long period of time (up to about 50 years), in the NBER database we observe at best the citations received up to 2006.

Following Hall, Jaffe, and Trajtenberg (2001, 2005), we correct for this additional source of truncation bias in the NBER data by dividing the observed citation counts by the fraction of predicted lifetime citations observed over the lag interval. More specifically, we scale up the citation counts using the variable "*hjtwt*" provided by the NBER patent database, which relies on the shape of the citation-lag distribution.

Although a larger number of patent citations is typically interpreted as associated with greater impact, the distribution of citations is also important. Therefore, again following Hall, Jaffe, and Trajtenberg (2005), we consider two more measures of patent activity: patent originality and patent generality. Following existing literature, patents that cite a wider array of technology classes of patents are viewed as having greater *originality*. We define a patent's originality score as one minus the Herfindahl index of the three-digit technology class distribution of all the patents that it cites. A patent with higher originality score draws upon a more diverse array of existing knowledge. Similarly, patents that are cited by a wider array of technology classes of patents are viewed as having greater *generality*. We then define a patent's generality score as one minus the Herfindahl index of the three-digit technology class distribution of all the patents that cite it. A patent with higher generality score is being drawn upon by a more diverse array of subsequent patents. We then aggregate individual patents' originality and generality scores to the firm-year level and compute the generality and originality scores for each firm-year. For firms that file no patents in a given year, their patent generality and originality scores are treated as missing for that firm-year.

We acknowledge that using patent activity to measure firm innovation is not without certain limitations. Patent activity is only one way in which a firm protects returns resulting from innovation. Many inventions are protected as trade secrets, such as the formula for Coca-Cola, and different industries have different innovation cycles and patenting propensities. Nonetheless, patents remain the most direct measure of the extent and quality of firms' innovation (Griliches, 1990), and the use of patent activity to measure of innovation productivity is widely accepted in the literature (Lerner, Sorensen, and Stromberg, 2011). We believe that adequate controls for heterogeneity in firm financials, firm industries, and location of real estate assets should lead to reasonable inferences applicable across firms in different industries.

1.2.2.3 Control Variables

We control for an array of firm characteristics previously shown to be significant determinants of innovation productivity. Hall and Ziedonis (2001) argue that the number of patent applications and the number of patent citations are positively related to firm size. We therefore control for firm size, as given by the natural logarithm of total assets (*Total Assets*); the results are robust to alternatively using the natural logarithm of net sales. Next, we control for R&D expenses scaled by lagged PPE (*R&D Expense*), as Atanassov (2012) shows that R&D expenditures play an essential role in a firm's innovation. We additionally control for the following variables: firm age, given by the natural logarithm of one plus the number of years between when firm *i* is listed and the year *t* (*Firm Age*); profitability, given by return on assets (*ROA*); growth opportunities, given by Tobin's Q (*Tobin's Q*); cash flow, given by the ratio of cash flow to lagged PPE

(*Cash*); liabilities, given by the leverage ratio (*Leverage*); investments in fixed assets, given by capital expenditures scaled by lagged PPE (*CAPX*); and product market competition, given by the Herfindahl index of the 3-digit SIC industry of the firm based on sales (*Herfindahl Index*) (e.g., Aghion, Bloom, Blundell, Griffith, and Howitt, 2005; Chemmanur and Tian, 2011; Atanassov, 2012; Chang, Fu, Low, and Zhang, 2013; He and Tian, 2013; Tian and Wang, 2013; Van Reenen and Zingales, 2013).

1.2.3 Summary Statistics

Columns (1) to (6) of Table 1 provide summary statistics for the variables used in the analysis based on the full sample. Looking at the innovation productivity measures, each year an average firm in our sample files approximately 4 patents, receives 36 citations for its patents, and has patent generality and originality scores of 1.0 and 2.0, respectively. The distributions of the four innovation productivity measures are highly skewed to the right, with the 75th percentiles of the distribution at zero.[2] We therefore winsorize these variables at the 99th percentile and use the natural logarithms of the number of patent applications, the number of patent citations, patent generality, and patent originality as our main innovation measures. To avoid losing firm-year observations due to zero values, we add one to the actual values when calculating natural logarithms.

An average firm has a real estate value of about 0.8. The distribution of this value is right-skewed as well, and thus we winsorize the real estate value at the 95th percentile and use the natural logarithm of one plus the real estate value as our main measure of the value of real estate assets in our analysis.

Turning to the control variables, an average firm has total assets of $672 million, ROA of 1%, Tobin's Q of 2.1, cash flow of 2%, leverage of 24%, R&D expense of 64%, capital expenditures of 37%, and Herfindahl Index of 0.15, and is 17.7 years old since its founding date. All of these control variables are winsorized at the 95th percentile.

[2] Firm-year observations with zero patents represent roughly 72.4% of our sample, which is comparable to the 84% reported in Atanassov, Nanda, and Seru (2007) and the 73% reported in Tian and Wang (2013) based on the universe of Compustat firms between 1974 and 2000 and VC-backed IPO firms between 1985 and 2006, respectively.

Columns (7) and (8) of Table 1 report mean values of the variables for high and low real estate value firms, respectively, where we divide the sample into high and low real estate value firms according to the median real estate value each year. Relative to low real estate value firms, firms in the high real estate value subsample have significantly higher innovation productivity measures, suggesting significantly greater investment in innovation. When we compare firm characteristics between the two subsamples, we find that firms with a higher real estate value are older and larger, they have higher profitability, fewer growth opportunities, higher leverage, more cash holdings, smaller R&D investments, and smaller fixed asset investments, and they operate in less competitive industries than their low real estate value counterparts.

Chapter 3 Empirical Results

1.3.1 Baseline Analysis

We first examine the effects of a firm's real estate collateral on innovation in a simple OLS multivariate regression framework. Specifically, we estimate the following model:

$$Ln(1+Innovation_{i,t}) = \alpha+$$

$$\beta Ln(1+REValue_{i,t})+\gamma REPrice_t^l+\delta Controls_{i,t}+\theta FE+\varepsilon_{i,t},(1)$$

where i indexes firms, t indexes years, and l indexes the MSA or state of the firm's headquarter. The dependent variable, $Innovation_{i,t}$, isone ofour innovation productivity measures (i.e., the number of patent applications, number of patent citations, patent generality score, and patent originality score).$Ln(1+REValue_{i,t})$,the natural logarithm of one plus the market value of real estate assets based on the MSA-or state-level price index, is our key explanatory variable. $REPrice_t^l$ controls for the real estate price index at the MSA or state level. $Controls_{i,t}$ comprises the set of control variables. In all specifications, wecontrol for two-digit SIC industry, year, and the MSA of location fixed effects (*FE*) to mitigate the concern that unobservable variables omitted from Eq. (1) that affect the value of a firm's collateral value might be correlated with innovation productivity. All of the standard errors of the estimated coefficients in Eq. (1) are clustered at the firm and year levels.

Table 2, Columns (1) to (4) report OLS panel estimation results examining the effect of a shock to a firm's real estate collateral value on innovation productivity as captured by the number of patent applications filed in a given year. In Columns (1) and (2), we measure the *RE Value* using the MSA-level real estate price index;

we find that the value of a firm's real estate collateral is positively and significantly associated with patent numbers. In particular, in Column (1) the coefficient on *Ln*(*1+RE Value*) is 0.314and it is statistically significant at the 1% level (t-statistic = 20).This result implies that an increase in real estate value leads to an increase in the number of patent applications (that is, an increase in the *quantity* of innovation) in the same year. In Column (2) the positive impact of real estate value on number of patents remains statistically significant at the 1% level when we include a number of control variables. In Columns (3) and (4), we measure *RE Value* using the state-level real estate price index instead of the MSA-level index, we find the positive and significant impact of real estate value on patents continues to hold. Note that the positive effect of real estate value on patents is economically large: when the *RE Value* increases from its mean value (0.80, measured using the MSA-level real estate price index) by one standard deviation (1.28), the average firm files $0.091\times[(1+4.02)/(1+0.80)]\times1.28=0.33$ new patent applications in the same year, which amounts to an8.2% increase from the mean value of patent number (4.02).

Table 2, Columns (5) and (6) report results for the effect of a shock to a firm's real estate value on innovation productivity as captured by the number of patent citations in a given year. In Column (5) the coefficient on *Ln*(*1+RE Value*) is again positive and significant at the 1% level, suggesting that an increase in real estate value leads to an increase in number of patent citations (that is, an increase in the *quality* of innovation)in the same year. In Column (6) we find that the positive impact of real estate value on patent citations remains statistically significant at the 1% level when we include a number of control variables. The positive effect of real estate collateral on patent citations is also economically large: when the *RE Value* increases from its mean by one standard deviation, the number of citations increases by $0.121\times[(1+36.17)/(1+0.80)]\times1.28=3.20$ in the same year for an average firm, which amounts to an 8.8% increase from the average patent citations (36.17).

In Table 3, we report OLS estimation results on the effect of a shock to a firm's real estate value on alternative measures of innovation productivity such as patent generality in Columns (1) and (2) and patent originality in Columns (3) and (4), respectively. Again, we find that real estate collateral value has a significant positive effect on patent generality and originality in the same year, with statistical significance at the 1% level. Economically, based on the estimated coefficients on *Ln(1+RE Value)* of 0.046for patent generality score in Column (2) and 0.070 for patent originality score in Column (4), a one standard deviation increase in *RE Value* from its mean will improve the patent generality and originality by $0.046\times[(1+1)/(1+0.80)]\times1.28/1=6.5\%$ and $0.070\times[(1+2)/(1+0.80)]\times1.28/2=7.5\%$ relative to their means, respectively, for an average firm. In summary, the findings in Table 3 further confirm our findings that an increase in the value of a firm's real estate collateral helps to improve its innovation productivity, with the positive effects both statistically significant and economically large.

The estimated coefficients on other control variables in Tables 2 and 3 are generally consistent with expectations. For example, larger firms and older firms have greater innovation productivity each year. Firms also have higher innovation productivity when they spend more on the R&D or reduce investment on physical assets (CAPX). In addition, firms with lower leverage and firms with more growth opportunities or cash are associated with greater innovation productivity, which is generally consistent with previous results.

1.3.2 Endogeneity Tests

Our evidence so far shows a robust positive effect of the value of a firm's real estate collateral on its innovation productivity. In this section, we then attempt to address the potential endogenous concerns and establish causality from real estate collateral to innovation productivity. Specifically, we seek to address two potential endogeneity concerns with this experiment: (1) real estate prices could be correlated with innovation productivity; (2) the decision to own or lease real estate might be correlated with firms' innovation productivity.

1.3.2.1 Concerns Associated With Real Estate Price

We use the instrumental variable (IV) approach to address the first endogeneity concern that real estate prices could be correlated with innovation productivity, following Chaney, Sraer, and Thesmar (2012). For example, firms that are more productive in innovation may demand more for local labors and products, which could push up local real estate prices. This is a standard reverse causality argument. In addition, the variations of real estate prices may proxy for real estate demand shocks, if the innovation activity of land-holding firms is more sensitive to demand shocks, this would bias our estimation of β in Eq. (1) as well.

In the first-stage of the IV regression, we predict the MSA-level real estate prices (*RE Price*) using the interaction of local housing elasticity provided by Saiz (2010), interacted with the nationwide real interest rate as in Himmelberg, Mayer, and Weisbach (2005). More specifically, we estimate the following first-stage regression to predict the *RE Price* of MSA *l* in fiscal year *t*:

$$REPrice_t^l = \beta \times Elasticity^l \times InterestRate_t + \gamma_t + \delta^l + \mu_t^l, \tag{2}$$

where $Elasticity^l$ denotes the elasticity of land supply for MSA l measuring the constraints of local land supply, $InterestRate_t$ denotes the nationwide 30 years real home mortgage rate adjusted by inflation for year t at which banks refinance home loans, γ_t denotes the year fixed effects, and δ^l denotes the MSA fixed effects.

The intuition is that the interest rate affects real estate prices differently for locations with different land supply elasticities. Demand for real estate increases as the mortgage rate decreases. For a location with a very high elasticity of land supply, an increase in demand will be likely to translate into increased quantity through new construction rather than higher real estate prices. In contrast, for a location with inelastic land supply, an increase in demand associated with a decrease in interest rate will be likely to translate into higher housing prices. Thus, the change in interest rate should have a larger impact on the real estate price and hence the market value of real estate collateral for locations with a lower land supplies elasticity.

Column (1) of Table 4 reports the estimation results of first-stage regression. As expected, the interaction of housing supply elasticity and interest rate has a positive and statistically significant impact on *RE Price* at 1% significance level. This result indicates that the positive effect of decreasing mortgage rate on *RE Price* is stronger in those MSAs with a lower elasticity of land supply.

Columns (2) to (5), Table 4 report the estimation results of the second-stage regressions of IV approach, where we calculate the *RE Value* using the predicted *RE Price* from the first stage, and we re-run our panel regressions in Eq. (1) for each of our measures of innovation productivity using the instrumented *RE Value*.

Column (2) of Table 4 reports the results when the dependent variable is the number of successful patent applications. The IV coefficient estimate on *Ln(1+RE Value)* is 0.068 when we include all of the control variables in the regression. The coefficient estimate here is slightly smaller than that based on OLS in Column (4) of Table 2, but is still statistically significant at the 1% level and economically large. Specifically, based on the IV estimation, a one standard deviation increase in *RE Value* will improve the patent numbers by 6.1% relative to its mean in the same year (0.068×[(1+4.02)/(1+0.80)]×1.28/4.02).

Similarly, Columns (3) to (5) of Table 4show that the IV coefficient estimates on *Ln(1+RE Value)* remain positive, economically sizable, and statistically significant at the 1% level, when we instead use patent citations, patent generality, and patent originality as our alternative measures of innovation productivity. In each case, a one standard deviation increase in *RE Value* increases an average firm's patent citations, patent generality score, and patent originality score by about 6% relative to their respective means in the same year for an average firm. The findings suggest that the positive effect of real estate collateral on innovation is unlikely driven by endogenous concerns related to real estate price and is consistent with the hypothesis that a positive shock to the value of real estate collateral improves firms' financing capacity and thus *casually* increases investment in innovation.

1.3.2.2 Concerns Associated With Real Estate Ownership

We then address the second endogeneity concern that firms' decision to own or lease real estate might be correlated with firms' innovation productivity. For firms those are more likely to own real estate, if their innovation is also more sensitive to fluctuations in real estate prices, our OLS estimation above may overestimate the effect of real estate collateral on innovation.

As a first attempt in addressing this ownership concern and establishing causality, we control for firms' observable characteristics affecting real estate ownership holdings decision interacted with real estate price in our multivariate regression specification of Eq. (1). If those controls which make firm more likely to own real estate also make firm more sensitive to fluctuations in real estate prices, controlling for the interaction between those controls and the contemporaneous real estate prices allows us to separately identify the collateral channel we are interested in.

In Column (1) of Table 5, we use the initial characteristics including firm age, firm size, ROA, as well as two-digit SIC industry dummies and MSA dummies to predict *RE Ownership*, a dummy indicating whether the firm reports any real estate holdings on its balance sheet in each year, in our first-stage regression. These controls are shown to play an important role in affecting ownership decision, consistent with the literature (Chaney, Sraer, and Thesmar, 2012).[3] We then calculate the interaction between the predicted *RE Ownership* and *RE Price*, and include this interaction term as an additional control variable in the second-stage panel regression of Eq. (1). Columns (2) to (5), Table 5 show that, after controlling for the endogenous decision of *RE Ownership*, the positive effect of real estate collateral on innovation remains statistically significant. The economic magnitudes are reasonably large, similar to those previously reported in Tables 2 and 3.

[3] As shown in Table 4 of Chaney, Sraer, and Thesmar (2012), older, larger, and more profitable firms are more likely to own real estate assets.

We recognize that there may be other unobservable determinants of a firm's real estate holding decision that impact our conclusions. Therefore, as a second attempt in addressing the endogenous ownership concern and establishing casual relationship, we additionally test whether the innovation productivity of firms holding real estate assets is more sensitive to changes in real estate prices than that of firms without any real estate assets, following Chaney, Sraer, and Thesmar (2012). Econometrically, we regress the innovation productivity measures on the MSA-level real estate prices for three different groups separately: non real estate purchasers, purchasers before the purchase of real estate, and purchasers after the purchase of real estate. If our previous findings are driven by the unobserved characteristics that affect both the land-purchasing decision and innovation productivity, the sensitivity of innovation to real estate price for purchasers before the purchase should be significantly larger than that for firms that do not own real estate assets, while the sensitivity for purchasers before the purchase should be similar to that for purchasers after the purchase.

As shown in Table 7, there is no significant relationship between *RE Price* and innovation productivity measures such as patents and patent citations for firms without real estate or for firms before the purchase of real estate. Instead, an increase in *RE Price* leads to significantly more innovation outputs only for firms with real estate assets after such assets have been purchased. We thus conclude the positive effect of real estate assets on innovation is unlikely driven by endogenous real estate ownership choice and is consistent with the hypothesis that a positive shock to the value of real estate assets casually increases investment in innovation through the collateral channel.

1.3.3 Innovation over Subsequent Years

Previously, we have examined the contemporaneous effect of real estate collateral on innovation. However, firm's investment in innovation is typically considered to be long-term investment which adds to the firm's stock to knowledge, and its benefits are likely to be persistent for several years in the future (e.g., Lerner, Sorensen and Stromberg, 2011). In this section, we thus analyze whether a shock to the value of real estate collateral in one year pertains to long-run effect on innovation and whether it would affect innovation over subsequent years.

Specifically, we estimate the inter-temporal effects of variation in real estate collateral value in year *t* on subsequent innovation measured over years *t*+1 to *t*+5, respectively, and report the results in Table 8. We also control for the same set of control variables as in Tables 2 and 3 as well as the two-digit SIC industry, year, and the MSA of location fixed effects. However, we do not report the regression coefficient estimates for the control variables and dummies in Table 8 of this section due to space constraint.

Table 8 shows that the positive effect of a change in real estate collateral value in year *t* on innovation productivity is strongest in year *t*+1. The positive effect then slowly decreases over time but remains positive, large, and significant over years*t*+2 to *t*+5. The economic magnitude of the positive effect continues to be economically sizable over the subsequent five years, and the coefficients on all of the inter-temporal regressions remain statistically significant at the 1% level. The findings here suggest that a change in the value of a firm's real estate assets has a persistent but slowly decaying positive effect on innovation productivity. Our findings thus are largely consistent with Hall, Griliches, and Hausman (1986), which studies the lag between R&D activities and patent applications and find that they move virtually simultaneously.

1.3.4 Economic Mechanisms

As previously described, we have found that an exogenous increase in the value of a firm's real estate collateral would casually increase its innovation productivity both contemporaneously and in the subsequent five years, which does not appear to be driven by endogenous concerns associated with real estate price and ownership. In this section, we further explore the possible underlying economic mechanisms through which the corporate real estate collateral affects companies' innovation productivity. Specifically, we partition our whole sample into subsamples according to financial constraint, debt financing dependence, and difficulty of innovation to examine whether our results vary across firms and whether these factors are possible underlying mechanisms through which real estate collateral affects innovation. The subsample regressions follow the baseline model specification of Eq. (1) which include all the control variables in Tables 2 and 3 as well as the two-digit SIC industry, year, and the MSA of location fixed effects, and we report the results in Tables 8 to 10.

1.3.4.1 Financial constraint

We have documented that an increase in the value of a firm's real estate assets can increase its innovation productivity. Recall that we posit that an increase in real estate value creates more innovation through the collateral channel. In the presence of financial constraints, constrained firms can use their real estate assets as collateral to finance their investment in innovation when they otherwise would be unable to do so. We hence expect such positive effects of real estate collateral to be stronger for constrained firms with costly and limited debt financing sources, as the appreciation of the collateral value of real estate assets improves firms' financing capacity. To further explore this financial constraint channel, in this section we empirically examine whether the positive effects of real estate collateral on innovation are stronger for constrained firms than for unconstrained firms.

We thus partition the full sample into two equally sized subsamples according to the KZ index measure of Kaplan and Zingales (1997) as a proxy for the extent of financial constraint. In each year, firms with a KZ index above the sample median are considered as financially constrained and vice versa. We then re-run our previous multivariate panel regressions separately for the two subsamples and report the results in Table 8. Consistent with our predictions, for the subsample of constrained firms, the regression coefficients on *Ln(1+RE Value*) are positive, economically large and statistically significant at the 1% level for all four measures of innovation productivity. Indeed, the economic magnitudes are about two times greater than those for the full sample reported in Tables 2 and 3. In sharp contrast, the coefficients estimates are insignificant for the subsample of unconstrained firms. Therefore, these findings confirm our hypothesis and show that the financially constrained firms with costly and limited financial resources benefit the most from the appreciation of real estate collateral value to improve their innovation.

As a robustness check, we use alternative measures such as corporate debt rating or paper rating as proxies for the extent of financial constraints, as suggested by the recent literature on financial constraint and investment (e.g., Denis and Sibilkov, 2010; Farre-Mensa and Ljungqvist, 2013).[4] We report the estimation results in Table IA3 of the Internet Appendix. We find that the findings in Table 9 are robust, and the positive effect of real estate collateral on innovation productivity continues to concentrate in the subsample of firms under financial constraints.

1.3.4.2 Debt Financing Dependence

The dependence on external debt finance provides another possible channel affecting the effect of real estate collateral on innovation. As the collateral value of real estate assets appreciates, financially constrained firm can borrow external debt as a fraction the collateral value of their real estate assets. We expect that constrained firms that need more debt finance will react differently compared to firms that primarily finance their innovation through equity. Actually, the literature (e.g., in Hart and Moore 1994; Chaney, Sraer, and Thesmar, 2012) shows that an increase in collateral value indeed leads to more issues of debt secured on the appreciated value of land holdings, which provides financing for investment in innovation. We thus expect that the positive effect of real estate collateral on innovation would be stronger for debt dependent firms which have relatively greater need for debt financing.

We check this prediction by splitting the full sample into two subsamples according to whether a firm has debt outstanding as a simple proxy for debt financing dependence. In each year, firms with debt are considered as debt dependent, and the rest of firms without any debt outstanding are considered non dependent. We then re-run our previous multivariate panel regressions separately

[4]Firms are classified as financially constrained based on debt rating (paper rating) if they have debt outstanding that year but their long-term (short-term) credit ratings are not available or below the investment grade.

for the two subsamples and report the results in Table 9. The findings again are consistent with our predictions. The regression coefficients on *Ln(1+RE Value*) are positive, economically large and statistically significant at the 1% level for the subsample of dependent firms but are insignificant for the subsample of firms without debt (i.e., non debt dependent firms). Again, these results lend further support to the view that a positive shock to the collateral value of a firm's real estate assets increases innovation productivity because it improves firms' debt financing capacity. Specifically, debt dependent companies that have greater needs for debt financing take advantage of the appreciation of real estate collateral value to improve their innovation.

1.3.4.3 Difficulty in Innovation

As discussed previously, an increase in the collateral value of real estate assets improves firms' innovation, because it helps to mitigate financial constraint and enhance debt financing capacity through alleviating agency costs and contracting frictions associated with the innovation process which is long, uncertain, often involving a very high failure probability. We thus expect that the positive effect of real estate collateral should be especially pronounced in hard to innovation industries where the innovation process is highly long, uncertain, involving high failure risk, and demanding large resources. If an increase in real estate collateral value indeed improves the financing capacity, then we expect to observe a larger impact of real estate collateral on innovation in these hard to innovation industries.

We split the full sample according to whether or not it is more difficult to innovate in the industry they belong to. Following the work of Hall, Jaffe, and Trajtenberg (2005) and Tian and Wang (2011), the full sample is classified into two subsamples based on patent technology class. Hard to innovation industries include pharmaceutical, medical instrumentation, chemicals, computers, communications, and electrical industries; and easy to innovation industries include software programming, internet applications, and other low-tech industries. In drug and electronics industries, innovation process is typically long, uncertain, failure risk is high, and resources demanded are large. On the other hand, it is relatively easy to create in software and low-tech industries. We then re-run our previous multivariate panel regressions separately for the two subsamples and report the results in Table 10. The findings again are consistent with our predictions. The regression coefficients on *Ln(1+RE Value*) are positive, economically large and statistically significant at the 1% level for the subsample of hard to innovation industries but are insignificant for the subsample of easy to innovation industries. These results suggest that the positive effect of real estate collateral for firm innovation is greater in industries in which innovation is more difficult to achieve, consistent with our prediction.

1.3.5 Additional Robustness Tests

To further ensure the robustness of our main results, we employ alternative model specifications, alternative subsamples and sub-periods, and alternative variable definitions. We report results of these additional robustness tests in Tables IA1 and IA2 of the Internet Appendix. All of the regressions include the same control variables and fixed effects as in Table 2 and Table 3.

In Panel A of Table IA1, we use alternative definitions for the innovation measures. We find that the effect of a change in real estate value on innovation is still positive and significant at the 1% level when using the four innovation productivity measures directly without the log-transformation, when using the natural logarithm of one plus the average citation number, generality score, and originality score per patent as the innovation measures, and when using a patent dummy and a citation dummy (equal to one when there is non-zero number of patent applications or non-zero number of citations for each firm-year, and otherwise zero) as the innovation measures.

In Panel B of Table IA1, we use alternative definitions of real estate collateral value. We find that the results are still positive and significant at the 1% level when using the real estate collateral value directly without the log-transformation, when using the market value of real estate assets based on the MSA-level real estate price index without normalization by lagged PPE, when using the logarithm of one plus the market value of real estate assets based on the MSA-level real estate price index without normalization by lagged PPE, when using the logarithm of one plus the market value of real estate assets based on the MSA-level real estate price index normalized by lagged total assets, and when using real estate ownership interacted with the MSA-level real estate price index, where real estate ownership is a dummy equal to one if a firm owns non-zero real estate assets, and zero otherwise.

In Panel C of Table IA1, we re-estimate the baseline analysis for different subsamples. We find that the results are similarly positive and significant when we exclude firms with zero patents and citations, and when we exclude firms located in the Silicon Valley Area (i.e., remove the firm-year observations within the San Jose-Sunnyvale-Santa Clara MSA).

In Panel D of Table IA1, we rerun the baseline analysis using different sub-periods. We continue to find positive and significant results when we limit attention to the 1993 to 1997 period (the pre-Information Technology bubble period),to the 1998 to 2000 period(the IT bubble period), and to the 2001 to 2004 period (after the IT bubble period and within the housing bubble period).

Table IA2 reports the cross-sectional relationship between firms' real estate value and Innovation outputs. The measures of innovation include each firm's annual average number of patents filed from 1993 to 2004 that are ultimately awarded and each firm's annual average citations, generality, and originality of all successful patent applications filed from 1993 to 2004. The independent variables include the firm-level sample average of the logarithm of one plus the market value of real estate assets based on the MSA-level real estate price index normalized by lagged PPE (RE Value) and other controls. We find that the coefficients on the sample average real estate value are positive and significant in all columns. The magnitudes of the coefficient estimates are similar to those reported in Tables 2 to 3. The estimates of other controls are also consistent with the previous panel regression results reported in Tables 2 to 3.

Chapter 4 Conclusion

In this paper, we investigate whether a change in the value of a firm's real estate collateral impacts its investment productivity. We find that, for the average firm, a one standard deviation increase in the value of the firm's real estate leads to about 8% increase in the number of patent applications in the same year, or 0.33 new patents. This positive effect holds for alternative measures of innovation such as the number of patent citations, patent generality, and patent originality. Further, this effect is strongest in the year following the shock to real estate value, but persists for at least five years following the shock to real estate value. These results are robust to controls for endogeneity, and concentrate among firms that are financially constrained, dependent on debt finance, and belonging to hard to innovation industries.

Overall, the findings in this paper suggest that in a developed capital market such as the U.S., firms face constraints to innovation. We document that a positive shock to the value of collateralized real estate assets can serve an important role in mitigating firms' financial constraints and thereby help increase innovation. These results improve our understanding of the link between debt financing capacity and investment in innovation.

Part II Dual-Class Shares and Corporate Innovation

Chapter 1 Introduction

Although the controversial nature of dual-class share structures has led several stock exchanges (e.g., Hong Kong and Singapore) to ban them completely, the debate is ongoing as to whether such share structures should be allowed in the future. Not only have dual-class shares been welcomed in the IPOs of young, hot technology firms like Facebook, LinkedIn, Groupon, and Alibaba, they are also used by mature firms like Ford Motors and Berkshire Hathaway. In the face of their increasing popularity, institutional investors are scrutinizing the downside of dual-class shares. CalPERS, for example, has decided to boycott all IPOs involving dual-class shares, arguing that dual-class stock misaligns the incentives of a company's shareholders and management, destroying shareholder value and unfairly benefiting the founders or executives who control the votes.[5] Supporters of dual-class shares, on the other hand, claim that a dual-class structure enables corporations to focus more on long-term than on short-term projects and thus supports innovation.

The academic community has produced ample empirical evidence of the negative effect of dual-class shares on shareholder wealth in public firms. This is consistent with the notion that, in some circumstances, controlling shareholders are willing to sacrifice public market share value to perpetuate their private benefits of control. Jarrell and Poulsen (1988), for example, show that dual-class shares exacerbate agency problems by protecting firms from hostile takeovers and giving managers greater power to guarantee job security and perquisites. Gompers, Ishii, and Metrick (2003), in constructing their original governance index, propose

[5] "Sorry CalPERS, dual-Class shares are a founder's best friend," *Forbes,* May 14, 2013.

that the adoption of dual-class shares is indicative of poor corporate governance. Likewise, a practitioner study by the Investor Responsibility Research Center (IRRC Institute, 2012) finds that, on average, firms with dual-class shares underperform firms with a one-share, one-vote standard over time. For newly listed IPO firms, Smart and Zutter (2003) also demonstrate that IPOs with dual-class shares exhibit poorer performance and trade at lower prices than IPO firms with single-class shares.

Yet, if dual-class shares are associated with inefficiency and lead to wealth destruction, why do we observe a proliferation of such shares in the market, especially in high-tech IPOs? Recognizing that innovation may be the most vital factor for building competitive advantages in technology companies, especially young firms, we employ several corporate innovation measures to explore whether the adoption of dual-class shares stifles corporate innovation. Besides being associated with inefficiency, dual-class shares are also often linked to severe agency problems (Jensen, 1986). For example, Masulis, Wang, and Xie (2009) show that dual-class shares protect managers or insiders by reducing the amount of outside shareholder monitoring. Our first hypothesis therefore posits that, consistent with the agency literature, dual-class shares tend to smother innovation. We also expect that their adverse effects on innovation will be more pronounced for firms that are particularly vulnerable to agency problems, such as mature firms, firms with large free cash flow, and firms with low takeover threats.

Product market characteristics matter for innovation and governance. We further hypothesize that dual-class shares will have smaller adverse effects on corporate innovation for firms operating in highly competitive product or innovation markets that face a greater cost of losing their innovation edge. In such a context, product and innovation market competition serve as effective alternative governance mechanisms that align managers' incentives with those of shareholders. Several recent studies show that product market competition helps to constrain managers and promotes value creation (Giroud and Mueller, 2010). Innovation is quintessential for high-tech firms (Porter, 1992). In these firms we predict that competitive pressures tend to offset the generally perverse entrenchment effects of dual-class shares.

To test these hypotheses, we use data widely accepted in the finance literature, a detailed NBER data set of over three million patents granted to U.S. public listed companies by the United States Patent and Trademark Office (USPTO) between 1976 and 2006. From this data set, we extract every patent granted each year for every firm, together with the citations for all of each firm's patents. We also use two alternative measures of innovation: patent originality and patent generality.[6]

We find that dual-class shares are negatively associated with innovation measures such as patent counts, citations, generality and originality. In a univariate test, for a public firm, having dual-class shares reduces patent counts by 0.69 per year (about 9%) and this difference is statistically significant. The negative effect of dual-class shares on innovation is marginally more pronounced for old firms than for young firms. We also show that the effect of dual-class shares is more pronounced for less financially constrained firms as measured by the KZ index (Kaplan and Zingales, 1997). This is consistent with a free cash flow agency effect. In addition, the negative impact of dual-class shares on innovation is highly significant for firms with low Tobin's Q ratios.

[6] Patent originality and generality are defined by Hall, Jaffe, and Trajtenberg (2005) as follows. Originality captures the extent that a patent cites previous patents that belong to a broad set of technologies. Generality captures the extent that a patent is cited by subsequent patents that belong to a wide range of technologies. These two variables are provided by Hall, Jaffe, and Trajtenberg (2005) and are available in the NBER patent database.

As regards to the importance of product or innovation market competition, we find that adopting dual-class shares has little effect on firms operating in industries in which innovation is difficult (hereafter, hard-to-innovate industries). In this case, the negative effect is driven mainly by firms operating in industries in which innovation is relatively easy. Hence, following Hall et al. (2005), we distinguish between firms by the degree of innovation difficulty in their product markets. Firms in hard-to-innovate industries require more time and resources to invest in innovation than those in easy-to-innovate industries, so the cost of innovation differs between the two (Tian and Wang, 2014). We also find that the negative effect of dual-class shares on innovation is less pronounced for firms operating in more competitive product markets as measured by the Herfindahl index.

Nevertheless, despite a significant and negative association between dual-class shares and corporate innovation, our findings could be driven by reverse causality; that is, firms with little innovation may be more likely to adopt dual-class share structures. We address this endogeneity concern by analyzing a subsample of firms that change from single-class shares to dual-class shares and demonstrate that such a shift precedes a significant decline in corporate innovation.

Our research contributes to the literature by providing new evidence on the role of dual-class shares in corporate innovation. Although prior literature links such share structures to the impairment of shareholder wealth and adverse corporate governance, the proliferation of dual-class shares adopted by young high-tech IPOs in the market warrants a systematic investigation. The evidence presented here suggests that dual-class shares stifle corporate innovation on average, especially in firms that are more vulnerable to agency problems. Dual-class structures do not, however, reduce innovation in firms operating in high-tech sectors or firms operating in competitive product or innovation markets. Nor do they reduce innovation in firms that are subjected to high takeover threats.

The remainder of the paper is organized as follows. Section 2 describes our data and empirical methods. Section 3 presents the main results and Section 4 reports the results of several robustness tests. Section 5 concludes with a brief summary and discussion.

Chapter 2 Data and Variables

2.2.1 Patent Data and Firm Characteristics

We obtain and construct our sample from the COMPUSTAT database for all US listed firms from 1970 to 2006, since the NBER patent data ends at the same year.[7]We require that the firms must have data in COMPUSTAT. We exclude firms that are involved in major acquisitions, as well as firms that are domiciled outside U.S. We also require firms to have financial data available on COMPUSTAT for at least three consecutive years. Finally, we exclude firms in the financial industries and trusts. These filters result in a final sample of 103,476 U.S. firm-year observations over the period 1970 to 2006.

In our analysis we control for an array of firm characteristics previously shown to be significant determinants of innovation productivity. Hall and Ziedonis (2001), for example, argue that the number of patent applications and the number of patent citations are positively related to firm size. We therefore control for firm size, measured by the natural logarithm of total assets. We control also for research and development expenses divided by total firm assets. R&D expenses play an essential role in financing firm innovation (Atanassov, 2013).We additionally control for the following variables: firm age, measured by years elapsed since the firm was first listed (Firm Age); profitability, measured by return on assets (ROA); growth opportunities, measured by Tobin's Q (Tobin's Q); the ratio of cash flow (Cash Flow) to total firm assets; the debt-to-assets ratio (Leverage); the rate of investment in fixed assets, measured by capital expenditures (CAPX) divided by total firm assets; the ratio of property, plant and

[7]NBER data comprise detail information on almost 3 million U.S. patents granted between January 1963 and December 1999, all citations made to these patents between 1975 and 1999 (over 16 million), and a reasonably broad match of patents to COMPUSTAT (the data set of all firms traded in the U.S. stock market).

equipment (PPE) divided by firm assets; and product market competition, measured by the Herfindahl index of the 3-digit SIC industry code based on sales (Herfindahl Index). The construction of this measure follows Aghion, Bloom, Blundell, Griffith, and Howitt (2005) and Aghion, Reenen, and Zingales (2013).

2.2.2 Innovation Measures

To form our sample of innovation measures, we collect annual information on innovation activity from the National Bureau of Economic Research (NBER) Patent Citation Data File. This data set contains detailed information on more than three million patents granted by the United States Patent and Trademark Office (USPTO) from 1976 to 2006. It provides information such as patent assignee names, numbers of patents, and numbers of citations received by each patent, patent application year as well as grant year, and patent technology class. One advantage of the NBER database is that it is likely unaffected by survivorship bias. As long as a patent application is eventually granted by the USPTO, it is attributed to the applying firm at the time of application even if the firm later is acquired or goes bankrupt. Moreover, because patent citations are attributed to a patent and not the applying firm, the patent granted to a firm that is later acquired or goes bankrupt can still receive citations long after the firm disappears.

Following the recent innovation literature, such as Seru (2014) for publicly traded firms and Lerner, Sorensen, and Stromberg (2011) for privately held firms, we measure a firm's innovation productivity using its patent activity, which indicates how effectively the firm transforms innovation inputs into outputs. With the information available in the NBER database, we use five measures of patent activity.

One measure of patent activity is the number of patent applications filed in a given year that are eventually granted. This captures the quantity of innovation output. We use the patent's application year instead of its grant year because, as Griliches, Pakes, and Hall (1988) argue, a patent's application year better matches the time of innovation than the patent's grant year. Patents, however, appear in the NBER database only after they are granted and it takes about two years on average for a successful patent application to be granted by the USPTO. Hence, many patent applications filed toward the end of our sample period (i.e., during 2005 and 2006) were still under review and had not been granted by 2006. We therefore also perform robustness tests that limit patent application data to the period from 1970 to 2004 to account for the truncation bias in patent application counts arising from the application-grant lag.[8]

Patent counts do not distinguish ground-breaking inventions from incremental technological discoveries. Hence, to further assess a firm's innovation productivity, we examine the number of patent citations received (cf. Hall, Jaffe, and Trajtenberg, 2001, 2005), thereby capturing the quality of innovation output. We exclude self-citations from the citation count, although our results hold when these are included. Although a patent can receive citations over a long period of time (up to about 50 years), in our NBER sample, citations received are at most through 2006. In the NBER patent database, the citation variable is adjusted for truncation bias (Hall et al., (2001, 2005)).[9]

Although more patent citations typically mean greater impact, the distribution of citations is also important. Therefore, we also use two more measures of patent

[8]Information on all these tests is available from the authors upon request.

[9]Hall et al., (2001, 2005) use an adjustment factor to address citation lag (both backward and forward lag).They correct for this additional source of truncation bias by dividing the observed citation counts by the fraction of predicted lifetime citations observed over the lag interval.

activity: patent originality and patent generality. Following existing literature, patents that cite other patents in a wider array of technology classes are viewed as having greater *originality*. A patent's originality score is defined by Hall et al. (2001) as one minus the Herfindahl index of the three-digit technology class distribution of all the patents that it cites. Patents with higher originality scores draw upon more diverse arrays of existing knowledge.[10] Similarly, patents that are cited by other patents in a wider array of technology classes are viewed as having greater generality. A patent's generality score is defined by Hall et al. (2001) as one minus the Herfindahl index of the three-digit technology class distribution of all the patents that cite it. Patents with higher generality scores are being cited by a more diverse array of subsequent patents. In the NBER patent data, each firm's annual patent originality and generality scores are calculated by adding up the individual scores across patents for the given year. For firms that file no patents in a given year the NBER database treats patent generality and originality scores as missing.

Besides the quantity, quality and the technology distribution of the innovation outputs, it is also important to know how firms' share class structures affect their innovation research and development efficiency. Following Hirshleifer, Hsu and Li (2013), we construct a measure of innovation efficiency equal to the number of patents divided by R&D investment (XRD). Specifically, for each firm-year we calculate innovation efficiency by taking the number of ultimately successful

[10]Hall et al. (2001) states, "Thinking of forward citations as indicative of the impact of a patent, a high generality score suggests that the patent presumably had a widespread impact, in that it influenced subsequent innovations in a variety of fields (hence the "generality" label). "Originality" is defined the same way, except that it refers to citations made. Thus, if a patent cites previous patents that belong to a narrow set of technologies the originality score will be low, whereas citing patents in a wide range of fields would render a high score".

patent applications filed by firm i in year t ($NumPat_{i,t}$) divided by firm i's weighted cumulative R&D investment during years$t$-4 through year t:

$NumPat_{i,t}$/ ($XRD_{i,t}$+ 0.8*$XRD_{i,t-1}$ + 0.6*$XRD_{i,t-2}$ + 0.4*$XRD_{i,t-3}$ + 0.2*$XRD_{i,t-4}$),

where $XRD_{i,t}$ indicates firm i's R&D investment in year t. We adopt this five-year cumulative R&D investment based on the assumption of an annual depreciation rate of 20% on R&D investment (cf. Chan, Laknoishok, and Sougiannis, 2001; Lev, Sarath, and Sougiannis, 2005). We consider also an alternative innovation efficiency measure that includes only contemporaneous R&D investment, $XRD_{i,t}$ in the denominator. The results are similar.

2.2.3 Identifying Dual-Class Firms

To develop our sample of dual-class companies, we begin with the sample in Gompers, Ishii, and Metrick's (2010) (hereafter, the GIM sample). The GIM sample was constructed from the universe of U.S. public firms from 1994 to 2002. It is the most comprehensive of all readily available data sets on dual-class firms. We expand the GIM sample period from 1994–2002 to 1970–2006 by drawing relevant dual-class data from the same primary sources that they used: Securities Data Company (SDC), S&P's COMPUSTAT, and the Center for Research in Security Prices (CRSP). The SDC's Global New Issues Database not only tracks corporate new issue activity from 1970 but flags those that have a separate class of common stock. In the CRSP database, we identify dual-class firms by their Committee on Uniform Security Identification Procedures (CUSIP) numbers. Following GIM (2010), those having the same 6-digit CUSIP number with different 2-digit extensions are considered to have dual-class share structures (cf. Gompers et al., 2010).Firms having a letter (A, B, C…) as part of their "share class” in the CRSP monthly database in any month of a year are also defined as dual-class firms in that year. Finally, because the CRSP data reports one specific stock issue of a firm while COMPUSTAT contains all shares of all classes of a firm’s stock, we compare “shares outstanding” in CRSP with “common shares outstanding” in COMPUSTAT (see Zhang, 2003). When the difference is more than 1%, we identify that firm as dual-class. Merging all of the above data together produces our final 1970–2006 list of dual-class firms.

Chapter 3 Results

2.3.1 Summary Statistics

Table 1A summarizes the innovation variables and firm characteristics for firms with single-class shares and those with dual-class shares. On average, single-class firms have an average of 7.32 patents per year. Firms with dual-class shares have an average of 6.63 patents per year. The other innovation measures such as patent citations, patent generality and originality, and innovation efficiency show a similar pattern. That is, on average, firms with dual-class shares are less innovative than single-class firms. Firms with dual-class shares also tend to be larger and older than single-class firms, and they operate in less competitive industries, those with a higher Herfindahl index.[11]

[INSERT TABLE 1A ABOUT HERE]

Table 1B reports the means and medians of innovation variables for firms with single-class and those with dual-class shares according to firm age, Tobin's Q, financial constraints, and hard-versus easy-to-innovate industries as well as high-versus low-tech industries. The univariate tests in Panel A indicate that older firms with dual-class shares have significantly fewer patents and citations than older firms without dual-class shares, while young firms do not differ significantly in innovation regardless of share class structure. According to Panel B, no matter whether firms have low or high Tobin's Q ratios, the means of the innovation variables for firms with dual-class shares are smaller than those for firms with single-class shares. Similarly, Panel C shows that firms with lesser degrees of financial constraints (low KZ indices) but with dual-class shares have significantly fewer patents and citations than those with single-class shares. Among financially

[11] The difference in the average Herfindahl indices is statistically significant, but small.

constrained firms, however, those with dual-class shares have higher mean numbers of patents and citations than those with single-class shares. This univariate test thus does not support the notion that dual-class firms are less innovative when firms are financially constrained. The univariate tests also indicate that in hard-to-innovate industries or high-tech sectors, firms with dual-class share structures do not have significantly lower innovation means than those without (see panels D and E).

[INSERT TABLE 1B ABOUT HERE]

2.3.2 Baseline Regression Results

Table 2 reports the baseline multivariate regression results of the association between dual-class share structures and innovation activities. These pooled ordinary least squares regressions control for both year and industry fixed effects. The main independent variable is a dual-class dummy, which equals one if the firm has dual-class shares in each year and zero otherwise. All regressions are controlled for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, cash flow, leverage, R&D expense, capital expenditure (CAPX), property, plant and equipment (PPE) and the Herfindahl index based on the three-digit SIC code.

[INSERT TABLE 2 ABOUT HERE]

As Table 2 shows, the estimated coefficients of the dual-class shares dummy variable are negative and significant in all four regressions using the four different measures of innovation. For example, having dual-class shares reduces the patent number counts of public firms by 5.28 per firm-year. Given the single-class sample mean of 7.32, this represents a 70% drop in patent counts per firm-year.

The coefficients of the other independent variables are consistent with prior literature (Tian and He, 2013). For example, innovation is positively related to firm size (assets), Tobin's Q, and R&D expenses.

[INSERT TABLE 3 ABOUT HERE]

2.3.3 Impact of Dual-Class Shares and Firm Characteristics on Innovation

Table 3 presents regression results similar to thoseinTable2. The focus in Table 3 is on the interaction term Dual-Class * Firm Age, which captures the impact of dual-class share structures on innovation for firms of different ages. The regression results show that the coefficients of Dual-Class * Firm Age are negative and marginally significant for patent number counts. This outcome shows that the negative effect of dual-class share structures on innovation is slightly more pronounced for old and mature firms than for young ones.

[INSERT TABLE 4 ABOUT HERE]

Table 4 presents regression estimates of the impact of dual-class shares on innovation for firms with differing growth opportunities. In this table we focus on the interaction term Dual-Class * Tobin's Q. The results show that the coefficients of Dual-Class * Tobin's Q are both statistically and economically significant. For example, in the regression of patent number counts reported in Column (1), the estimated coefficient of Dual-Class * Tobin's Q is 2.99 and for Tobin's Q is 0.407. The standard deviation of Tobin's Q for single-class firms is 3.3 and for dual-class firms it is 2.24 (see Table 1A), respectively. Hence, an increase of one standard deviation in Tobin's Q will result in an increase in patent counts of 2.24 * (0.407 + 2.992) = 7.61 per year for dual-class firms and of 3.3 * 0.407 = 1.34 for single-class firms.

[INSERT TABLE 5 ABOUT HERE]

Table 5 presents regression estimates of how the impact of dual-class shares on innovation varies with the KZ Index, our measure of financial constraints. The coefficient of the interaction term Dual-Class*KZ Index is of principle interest here. This coefficient shows how the impact of dual-class shares on innovation varies for firms with differing degrees of financial constraints. The estimated coefficients of Dual-Class * KZ Index are all positive and for two of the regressions they are marginally significant. This is consistent with the intuition that agency problems are exacerbated by dual-class share structures when insiders are not financially constrained, i.e., for firms with low KZ indices.

[INSERT TABLE 6 ABOUT HERE]

In Table 6we present regression estimates of how firm cash flow affects the impact of dual-class shares on firm innovation productivity. As in Tables 3, 4, and 5, we focus on the interaction term between the dual-class dummy variable and the moderating variable of interest, in this case, Cash Flow-to-Assets. The regression results show that the estimated coefficients of Dual-Class * Cash Flow/Assets are all negative but the estimate is statistically significant only for the Patent Number regression. These results, therefore, are consistent with the notion that dual-class shares depress innovation activity to a greater extent for firms with high internally generated cash flow, but the evidence is weak.

2.3.4 Impact of Dual-Class Shares and Industry Characteristics on Innovation

The recent proliferation of firms with dual-class share structures in the high-tech industries motivates the analysis presented in this section. We investigate whether dual-class share structures encourage or depress innovation in high-tech industries. We adopt Hall and Lerner's (2009) taxonomy where the high-technology sector comprises pharmaceuticals, office and computing equipment, communications equipment and electronic components.

[INSERT TABLE 7 ABOUT HERE]

The relevant regression results are presented in Table 7. Note that the estimated coefficients of the high-tech industry dummy variable are all positive and highly significant. This is unsurprising. It is more interesting that the depressing effect of dual-class shares on innovation is greatly moderated for high-tech firms. The estimated coefficients of the interaction term Dual-Class * High-Tech are all positive. In three of the four regressions they are statistically significant. Moreover, the magnitudes of the coefficient estimates indicate that the impacts of dual-class shares on Patent Number, Citation Number, and Originality are substantially offset for high-tech firms. We perform a t-test of the hypothesis that the sum of the coefficient on the dual-class shares variable and on its interaction with the high-tech firms variable is zero. We cannot reject this hypothesis at conventional significance levels for patent counts or patent originality. The t-statistics are -1.57 and -1.54, respectively. We do reject the hypothesis for patent citations and patent generality with t-statistics of -2.37 and -3.42, respectively. These results, though somewhat mixed, indicate that dual-class share structures affect innovation for high-tech firms to a lesser degree than for single-class firms. This may help to explain why high-tech companies seem increasingly willing to adopt dual-class share structures.

[INSERT TABLE 8 ABOUT HERE]

Table 8 presents regression results similar to those in Table 7. The focus in this table is on the interaction term Dual-Class * Hard-to-Innovate. According to Hall, Jaffe, and Trajtenberg (2005), the Hard-to-Innovate industries are pharmaceuticals, medical instrumentation, chemicals, computers, communications, and the electrical industries. The estimated coefficients of the Dual-Class * Hard-to-Innovate interaction terms are positive and statistically significant for three of the four regressions. Moreover, the magnitudes of the coefficient estimates indicate that the impacts of dual-class shares on Patent Number, Citation Number, and Originality are substantially offset for firms in hard-to-innovate industries. We perform a t-test of the hypothesis that the sum of the coefficient on the dual-class shares variable and on its interaction with the hard-to-innovate variable is zero. We fail to reject this hypothesis for patent counts, patent citations, or patent originality though we do, again, reject the hypothesis for patent generality.[12] These results suggest that the negative effects of dual-class share structures for firms in hard-to-innovate industries are relatively small.

[INSERT TABLE 9 ABOUT HERE]

2.3.5 Impact of Dual-Class Shares and Market Characteristics on Innovation

Prior research indicates that insiders or executives adopt dual-class share structures to secure their own jobs and benefits when facing external takeover threats (Bebchuk and Cohen, 2003). For this reason, we examine how the effects of dual-class shares on innovation vary for firms with different exposures to takeover risk. We rely on takeover measures that are unrelated to firms' own characteristics. One useful proxy for takeover risk is Bebchuk and Cohen's (2003)

[12] The t-statistics are -0.59, -0.95, and -1.19 for patent counts, patent citations, and patent originality, respectively, and -3.05 for patent generality.

state-level index of anti-takeover laws. This index takes integer values from zero to five, with higher values corresponding to more restrictive takeover laws and, hence, lower implied external takeover risk. In the regression analysis we focus on the interaction term, Dual-Class * Anti-Takeover Index.

We report the regression results in Table 9. The estimated coefficients of the interaction term are negative in three of the four regressions and statistically significant for Patent Number and Citation Number. These results show that dual-class firms facing low takeover threats have fewer patents and patent citations than those operating in environments subject to high takeover threats. The evidence suggests that takeover threat mitigates the negative effects of dual-class shares on innovation. Note also that the estimated coefficients of the Anti-Takeover Index variable itself are all negative and significant. This indicates that barriers to external takeovers are negatively associated with innovation productivity for firms in general.

[INSERT TABLE 10 ABOUT HERE]

In addition to takeover threats, product market competition provides another monitoring mechanism that serves to constrain self-serving managerial behavior. We propose that firms operating in relatively uncompetitive markets may be susceptible to managerial abuse and that this may lead to fewer resources being allocated for innovative activities. We use the Herfindahl Index as a proxy for the level of product market competition. In the regression analysis the coefficient of the interaction term, Dual-Class * Herfindahl Index, is of principle interest. The regression results are summarized in Table 10. The Dual-Class * Herfindahl Index coefficients are all negative. In three of the four regressions the estimates are statistically significant. These results imply that firms with dual-class shares that operate in relatively uncompetitive product markets are less innovative than dual-class firms facing stiffer product market competition. The estimated coefficients of the Herfindahl Index itself, however, are positive. This suggests that innovative output is greater in concentrated industries. Hence, the overall effect of product market competition on innovation is unclear.

2.3.6 Robustness Check

One concern about our evidence on the negative association between dual-class shares and innovation is the possibility of reverse causality, in the sense that less innovative firms may choose to adopt dual-class share structures. To address this possibility, we conduct a test using a subsample of public firms that switched from single-class to dual-class share structures. This sample enables us to present evidence bearing on the possibility of reverse causality.

The results, reported in Table 11, show that the estimated coefficients of the Dual-Class dummy variable are all negative and highly significant. Since the sample includes only firms that changed share class structures these results imply that innovation outputs declined after the switch to dual-class. The magnitude of these outcomes is also economically significant. The evidence suggests that a change from single- to dual-class share structures is associated with a decline in patent counts of 4.76 per firm-year. Given the single-class sample mean (patent counts) of 7.32, this represent a decline of 65%. We observe a similar decline for citation counts. These results help to mitigate concerns about reverse causality. We cannot, however, completely rule out an alternative explanation that firms anticipating declines in innovation voluntarily adopt dual-class shares as a defence mechanism.

[INSERT TABLE 11 ABOUT HERE]

Taken together, the above results raise an important question. Through which channels do dual-class share structures affect innovation? We examine this issue using R&D expenses deflated by the book value of total assets as the dependent variable. These estimates, reported in Table 12 Column (1), indicate that dual-class shares have a negative effect on R&D expenses. This implies that firms with dual-class share structures spend relatively less on research and development.

[INSERT TABLE 12 ABOUT HERE]

Column (2) of Table 12shows the results using the subsample of public firms that switched from single-class shares to dual-class shares. This is to ascertain whether the results in Column (1) are due to reverse causality. The estimated coefficient of the dual-class dummy is negative but not statistically significant.

[INSERT TABLE 13 ABOUT HERE]

As a corollary, we next examine innovation efficiency. We measure innovation efficiency by the number of patents applied for and eventually granted each year divided by the R&D expense of previous years as in Hirshleifer et al., (2013). Table 13 summarizes the regression results using innovation efficiency as the measure of innovation. Results for the full sample are reported in column (1). The estimated coefficient of the dual-class shares dummy variable is negative and statistically significant. Column (2) of Table 13shows the results for the subsample of public firms that switched from single-class shares to dual-class shares. We perform this test to ascertain whether the results in Column (1) are due to reverse causality. For this alternative measure of innovation, the estimated coefficient of the dual-class dummy is negative and statistically significant. Results from Table 13 are consistent with the hypothesis that dual-class share structures tend to decrease innovation.

[INSERT TABLE 14 ABOUT HERE]

In Table 14 we report regression results for dual-class on innovation efficiency for young versus old firms, hard- versus easy-to-innovate industries, high- versus low-tech industries and high versus low takeover threats. The results show that the negative effects of dual-class shares are associated with older firms, firms operating in easy-to-innovate industries, firms in low-tech sectors, and firms in states with low takeover pressure. We interpret these results to mean that dual-class shares lead to low innovation efficiency in firms characterized by high levels of agency problems. For firms in the other subsamples, the estimated coefficients of the dual-class share dummy are statistically insignificant.

Chapter 4 Conclusion

In building competitive advantage, especially in high-tech firms, innovation is quintessential. Recently, there has been a proliferation of high-tech IPOs adopting dual-class share structures. Our research investigates the effects of dual-class share structures on corporate innovation. The empirical analysis provides strong evidence that dual-class shares are negatively associated with all four innovation measures (patent and citation counts, patent generality and patent originality). We also find similar results for the relationship between dual-class shares and innovation efficiency. These results support the hypothesis that dual-class structures tend to stifle innovation.

The negative effects of dual-class share shares on innovation are more pronounced for firms with looser financial constraints, those with low takeover pressure, and those operating in less competitive product markets. These findings imply that agency problems are likely to be exacerbated by the adoption of dual-class shares because such share structures provide insiders or executives with a power of control that is greater than warranted by their ownership.

Surprisingly, however, dual-class shares seem to have almost no negative effects for firms operating in high-tech and hard-to-innovate industries. Similarly, dual-class firms that operate in markets with high takeover threats and intense competition have innovation outputs that are significantly higher than those that are not subject to such market pressures or discipline. This implies that the nature of the product market and the cost of innovation play a complementary role to corporate governance in mitigating the agency problems arising from the use of dual-class shares.

Overall, our research provides important insights on the increasing popularity of dual-class shares among high-tech companies. Our evidence highlights the role that market characteristics play in determining the effects of share class structures on corporate innovation.

Part III Sarbanes-Oxley and Corporate Innovation

Chapter 1 Introduction:

The history of regulation on markets and firms shows significant social and economic costs, including substantial and unintended effects on industrial competitiveness (Hahn, 1998). These effects on firm performance have been examined mostly through an economist's lens, but have lacked development in research. In recent years, and especially with regards to the advent of regulations such as the Sarbanes-Oxley Act, the effects on innovativeness have started to be more keenly felt (The Economist, 2007). This is particularly worrisome since economies and firms are becoming increasingly competitive with time, and technological change (i.e., innovation) is increasingly an integral aspect of that competitiveness. As such, regulations can now not only increase the costs of doing business, but can also affect firms' global competitiveness (Hahn and Hird, 1991; Wall Street Journal, 2012).

Despite this emerging concern, we still lack wider and more thoroughly explored understandings of the effects of economy-wide regulations on value creating activities such as innovation. Regulations simply have not been studied as much in the innovation and management literature, especially with regards to their effects on decision-making. This with the exception of studies on the stimulative effects of specific regulations on innovation, such as ones in the environmental arena, and with regards to university patenting via the Bayh-Dohl Act (Mowery et al, 2001). To address this gap, we will examine the question of one of these major hidden costs, which is the effect of certain generalized regulations -such as the Sarbanes-Oxley Act, addressed to corporate governance - on the innovativeness of business.

The Sarbanes-Oxley Act of 2002 was one of the most far reaching regulations in recent decades. It was enacted to curb the worst of corporate excesses and to bring a denouement to the series of corporate governance scandals seen with the likes of the Enron and World.com cases of corporate misconduct. SOX legislation ushered in an era of increased power and accountability with external board members, audit controls, and overall responsibilities and greater liabilities for corporate leadership and auditors alike. However, the regulation's "heavy-handed" influence also became the focus of corporate concern early on. The former chairman of the Securities Exchange Commission (SEC), William Donaldson, wondered if *"...by unleashing 'batteries of lawyers across the country' the legislation would lead to a 'loss of risk-taking zeal' due to a "huge preoccupation with the dangers and risks of making the slightest mistake"*. It was observed that there was a decrease in IPOs, starting in 2008 and running through 2011 (Wall Street Journal, 2012). Was corporate innovation, and innovative risk-taking, put at risk by SOX?

With this practical question in mind, we sought to understand the negative effects of SOX on firm-level innovation, as an unintended effect of the regulation.[13] Early studies suggested that the effects of SOX have been benign, but as with studies of other regulations, these were often predicated on the *direct costs* of compliance and involved measuring these effects against the public benefits, or framing them in equity (across companies) terms(Coates and Srinivasan, 2014). Recent studies have been concerned with the regulation's effect on corporate competitiveness, including by way of firms' ability to innovate (Shadab, 2008,

[13]There are different types of regulation, and while these having differing effects on corporate decisions, they also have the generally common effect of increasing the costs of doing business. This is particularly the case for environmental regulations (Coeurderoy and Murray, 2008; List et al., 2003). SOX legislation may fall in this category.

Bargeron et. al., 2010, Waters, 2013). In particular, SOX was shown to be affecting US corporations' R&D investments by causing them to assume less risk and hoard more cash (as shown to happen after the legislation) (Bargeron et al., 2010).We contribute to this line of research by examining the SOX legislation's effect on *innovation output,* as seen in evidence on corporate patents. The problem is that firms respond to their institutional environment and in doing so may attend to other interests than to the firms' and their managers' interests (Jensen and Meckling, 1976). The question is, in the interests of guarding against corrupt practices, has the SOX's enhancement of firm's governance structure now lessened managers' natural risk-taking tendencies?

In section 2, we discuss the background behind our hypothesis - that the enactment of SOX stifles innovation. In section 3, we build on established methodology in the innovation literature, using patent filings and innovation efficiency as a measure of corporate innovations, directly testing the hypothesis (Hall, et al, 2001; Hall, et al., 2005). In section 4, we discuss our findings. In our baseline regression, we find that after controlling for a number of concomitant variables like firm size, firm age, return on assets (ROA), measure of firm value (Tobin's Q), amount of cash holdings, leverage, capital and R&D expenditures, and measure of industry concentration (Herfindahl Index) with both industry and year specific fixed effects, the enactment of Sarbanes-Oxley legislation has a significant negative impact on firm innovation. [14] We find an unmistakable downward spiral of innovation measured in terms the number of patents, the number of citations of patents per year, and the generality and originality scores of the patents filed each year since the enactment of SOX. Controlling for firm size,

[14]The result is robust to different quintiles of firm asset size (or log of firm size) and value (measured by Tobin's Q) although it is much more pronounced for the biggest quintile of firms.

firm value, levels of governance, and high tech sectors, the number of patents dropped significantly between the pre- and post-SOX regimes. Finally, in section 5, we discuss the possible mechanisms underlying management decision-making and corporate behavior with the help of the corporate governance, innovation and management literature.

Chapter 2 the Nature of Regulatory Influences on the Firm

To understand the theoretical means by which how SOX may impact negatively on innovation, we review some of the pertinent literature. One pertains to theories relating to the causes and effects of regulation. It is a fundamental tenet of modern economics that negative externalities or spillovers can be corrected by regulations, but at certain direct costs. Since the advent of neoclassical economics at the time of Adam Smith in the 1700suntil the current era, most regulation shave been of the form that "protect the public interest" by taking the public's interest directly into account by making the competition fairer (Krugman, 2011). Regulations were generally designed to counter various negative aspects of behavior among economic agents causing negative spillovers or externalities to society at large.[15]Since the beginning of the last century, a number of cases of industry misconduct or behavior led to regulations that sought to rein in these business excesses, usually promulgated for one specific industry at a time. The earliest and more famous cases were more related to problems of industry structure and concentration, leading up to the various episodes of antitrust regulation, where "fair competition" was the desired regulatory outcome (Hart, 2001).[16]

[15]One major feature of regulation involves the internalization of pollution-type externalities caused by private sector activities, as was seen in the variety of environmental and health laws signed into effect over the past few decades, one of the earliest being the 1963 Clean Air Act.

[16]The Interstate Commerce Act of 1887 was one of the first, to regulate railroads. While the theory of regulation was largely an issue in the public administrative and legal disciplines, and subjected to economics so far as cost-benefit analyses were warranted, during the 1970s, self-interest was incorporated into the economic theory of regulation, intertwining of the interests of the industry and the regulators themselves (Pelztman et al., 1989; Posner, 1974). In practice, this sort of individualistic bent was exacerbated in the socio-political sphere with the rightwing political lurch and deregulation impulses of the 1980s. To some degree, this has been associated with the unfettered (*Laissez-faire*) nature of business practice that ensued in the 1990s and later, with "business deal making" (mergers and acquisitions in particular) becoming *de rigueur*. While few theories can explain these pendulum "lurches" in the political sphere, by coupling management theory with behavioral models, we can in limited fashion understand why firms' leaders act the

Underlying all of these traditional notions of regulation are two conceptions of behavior. The first is that increasing industry power (such as that accrued from industry concentration measured by *Herfindahl* type indices) could lead to misconduct by economic agents. Misconductor inappropriate action can be brought on by a variety of factors, including cultural (e.g. "bad" corporate cultures and poor ethics), psychological (in way of increased expectations) (Akerlof, 1970; Aguilera, 2005; Greve et al., 2010; Mishina et al., 2010), and personality-based (Hayward and Hambrick, 1997) ones. The second idea inherent in notions of regulation pertains to the ability of regulations to "target" certain outcomes and to then compel firms to shift their strategy in the desired directions. In the environmental arena for instance, "command and control" environmental regulations enacted to create emissions standards were expected to lead not only to compliance, but in the extreme, to technological innovation.[17]

That regulations could easily fall astray of their intended purposes is not new. While most of the costs expected of regulation are the direct costs of compliance (as is commonly seen in environmental regulations), other hidden (or implicit)costs are derived from the unintended consequences of the regulations and unanticipated behaviors instigated. Regulations have historically also been known to have unintended consequences, including the Prohibition Act of 1920 - enacted ostensibly to control alcohol, with the consequence being increased underground and criminal activity. The series of banking regulations enacted in the wake of the Great Depression, starting with the Banking Act of 1933 and the

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way they do (e.g. Li and Tang, 2010; Mishina et al., 2010), and in the case of our study, understand how regulations may come to constrain their decision making on innovative actions.

[17]The "Porter hypothesis" (Porter and Van der Linde, 1995), described even earlier by Ashford and others (Ashford and Heaton, 1983; Ashford et al., 1985), suggested that firms would innovate to get out of regulatory mandates.

accompanying Glass-Steagall Act (1932), some of which were eventually partially repealed.[18]Thus, while regulations as these initially have a well-intended social purpose, their typically heavy hand and overall coarse manner by which they target perceived problems makes it difficult for them to achieve the desired behavior.

The SOX follows in the long tradition of the governance of business behavior and regulation of misconduct. Although white collar in nature, the ostensibly criminal acts committed by Enron, World.com and other corporate leaders was determined to be the result of a lack of independent board oversight on activities, and the insufficient powers of auditors. Articles in the SOX legislation resolved to strengthen these poor governance controls, at the expense of CEOs' independence. The most typical and direct of mechanisms cited is the increased cost of compliance - for publicly traded firms and smaller firms alike (Coates and Srinivasan, 2014).

The enactment of the SOX legislation in July 2002 provides us with a natural experiment under two different regimes (pre and post SOX) to evaluate the impact of SOX on corporate innovation. As previously noted, SOX has been shown to have decreased R&D investments, and presumably, risk-taking (Bargeronet al., 2010; Dey, 2010). Our premise is that decisions on the input side such as these (R&D investments) will translate into specific effects on the output side: decreased patenting. Since innovation is costly, involving a process that is

[18]Even while environmental regulations were in some ways found to be incentivizing of innovation, another dominant strand of the discourse in public policy shows perverse effects on business behavior. Environmental regulations that "target" behaviors with increased standards may lead to unintended consequences such as the shifting of "dirty plants" across borders (Coeurderoy and Murray, 2008). Thus, such regulations affect not only direct decision-making on investment in pollution control equipment, but a higher level strategic decision such as whether to "escape" such regulations, or to invest in such R&D (with one study finding the former effect, but not the latter [Jaffe and Palmer, 1997]).

long, idiosyncratic, uncertain, and often with a high probability of failure (Holmstrom, 1989), SOX's effect on risk-taking can make such a process less attractive (Bargeron et al., 2010).Although the exact mechanisms have yet to be explored or discussed, it is presumed that the very same instruments that SOX uses to guard against misconduct - increasing auditing, outside director oversight, and the specification of liabilities – can also be disruptive of corporate innovation.[19] We thus hypothesize the following effect of SOX on innovation:

Hypothesis 1. The enactment of SOX has a negative impact on corporate innovation.

[19] For example, SOX does this through specific governance mechanisms such as shaping the corporate's board of directors. Specifically, several sections of the legislation expand the role of and expanded liability of independent directors. SOX legislation mandates US listed firms to have significant (75%) external or independent board members.

Chapter 3 Data and sample summary

3.3.1 Data

The voluminous literature on the economics of innovation and the strategic management of innovation both widely accept patents as a primary measure of innovative output. [20] Notwithstanding the limitations, patents remain the most direct measure of the extent and quality of firms' innovation (Griliches, 1990), and the use of patenting activity to measure of innovation productivity is widely accepted in the extant literature (Lerner et al., 2011). We use patent innovation data on publicly listed US corporations from Harvard University's patent database. This database includes all patents filed and granted by the United States Patent and Trademark Office (USPTO) from 1990 to 2009. The database provides detailed information on patent assignee (owner) names, the patent number, and a patent's 3-digit technology class. For specifying the year of the patent, we use the patent's application year instead of grant year, following Griliches et al (1988).

If patents are measures of innovative output, R&D expenditures remain the main input to innovation, in effect, measuring the initial commitment to innovate. Our second measure of innovation, proposed by Hershleiferet al. (2013), relates this to patents: *innovation efficiency* (*IE*). We construct this measure by taking the number of patents scaled by the previous year's R&D expenditure. Specifically, IE is calculated by taking the number of patents of firm *i* applied in year *t* which were eventually granted ($NoPat_{i,t}$) scaled by firm *i*'s cumulative R&D investment in fiscal year ending from year *t-4* through year *t*:

$$\mathrm{NoPat}_{i,t} / (\mathrm{XRD}_{i,t} + 0.8{*}\mathrm{XRD}_{i,t-1} + 0.6{*}\mathrm{XRD}_{i,t-2} + 0.4{*}\mathrm{XRD}_{i,t-3} + 0.2{*}\mathrm{XRD}_{i,t-4}),$$

[20] Nevertheless, the number of patents is but only one measure of innovative productivity. For example, some inventions are protected as trade secrets, such as the formula for Coca-Cola, and others like software are protected in other ways. Besides different industries have different innovation cycles and patenting propensities.

where $XRD_{i,t}$ indicates firm *i*'s R&D investment in fiscal year ending in year t, and so on. We adopt this 5-year cumulative R&D investment based on the assumption of an annual depreciation rate of 20% on R&D investment, following from Chanet al. (2001) and Levet al. (2005). Innovative efficiency highlights the effectiveness of R&D expenditures in terms of the number of patents that are applied for (successfully) for every unit of an exponentially smoothed average R&D dollar, i.e. "…innovative bang for the R&D buck…"

Any corporate decision in a firm is affected by various external and internal factors, and innovation is no different. Identification of factors that are instrumental in innovative efficiency requires controlling for concomitant variables that might affect innovative activity in a firm. The control variables are collected from the COMPUSTAT database. These control variables include size (*Total Assets*), firm age, book to market, R&D expenses scaled by lagged PPE, return on assets (*ROA*); growth opportunities (*Tobin's Q*), cash, leverage, capital expenditures scaled by lagged PPE (*CAPX*); and product market competition, given by the Herfindahl index of the 3-digit SIC industry of the firm based on sales (*Herfindahl Index*). These control variables are used in the extant literature (e.g., Hall and Ziedonis, 2001; Aghion, et al. 2005; Chemmanur and Tian, 2011; Atanassov, 2012; Chang et al., 2015; He and Tian, 2013; Tian and Wang, 2013; Van Reenen and Zingales, 2013).[21]

[21] The most relevant control to the innovation literature is firm size. Ever since Schumpeter, differential firm size has always been known to have an effect on the ability to innovate (Cohen and Levin, 1989). SOX has already been shown to have differential impact on firms at least in terms of costs of compliance and the likelihood of firms listing in the U.S. (Coates and Srinivasan, 2014; Piotroski and Srinivasan, 2008).Along with firm size, firm age is also a historically relevant measure, given that age has implications for firms' ability to innovate, particularly with regards to their explorative innovative ability (Sorensen and Stuart, 2000). Our approach also examines the possibility not covered in Bargeron et al., (2010) that under SOX, R&D might have become more efficient which is beneficial to firms without impacting innovation significantly (Hirshleifer et al., 2013).

3.3.2 Summary

Figure 1 depicts the general patterns of innovation 3 years before and 3 years after the 2002enactment of the SOX legislation. We calculate the sample mean of patents and innovation efficiency of all firms each year. Figure 1 shows a noticeable pattern with both measures of innovation decreasing after the SOX event. In particular, the number of patents shows an increasing trend before 2002 and a decreasing pattern after the enactment of SOX. The caveat is that not all parts of the SOX legislation came into immediate effect. However, it can be conjectured that firms started taking decisions in advance of the legislation and that were in anticipation of the impending but phased rollout of SOX and its provisions.

Table 1 reports the summary statistics of the innovation variables and control variables 3 years before and 3 years after the year of the initial SOX legislation. The sample mean of patents before SOX was0.41; after SOX the mean dropped to 0.40but this was not a statistically significant drop. The innovation efficiency measure drops in the post SOX period by 0.03, a near 50% drop from pre-SOX value that was statistically significant. We further note that the sample means of controls such as firm size, ROA, Tobin's Q do not exhibit difference before and after SOX legislation. Interestingly, without conditioning on other control variables, neither R&D expenses nor CAPEX show significant drops after the advent of SOX legislation.

Table 2 reports the correlation matrix of all variables. Both the measures of innovation,, patent count and innovation efficiency, are not highly correlated with each other at 0.063. Firm size has non-zero correlations with the measures of innovation; R&D expenses have correlations of 0.37 with innovation measures such as patents.

Chapter 4 Empirical Results

3.4.1 Baseline Analysis

We first examine what factors drive firm innovation in a multiple regression framework for panel data. Specifically, we estimate the following model:

$$Innovation_{i,t} = \alpha + \beta\, SOX\, signal + \delta Controls_{i,t} + \theta FE + \varepsilon_{i,t}\ , \quad (1)$$

where i indexes firms and t indexes years. The dependent variable $Innovation_{i,t}$ is one of our innov ation measures (i.e., the patents' innovative efficiency). *SOX signal* is a dummy or binary variable that equals one if year is 2003, 2004, and 2005, and zero otherwise.

Table 3 reports the baseline OLS regression results as specified in model (1). The regression of coefficient estimate for *SOX signal* is -0.115 when the dependent variable is the logarithm of patents, and -0.055 when the dependent variable is innovation efficiency. Holding all other control variables constant, the number of patents drops by approximately 11.5% after the enactment of SOX. In similar vein, *ceteris paribus*, innovative efficiency drops by 0.055 patents for every average dollar of R&D expenses spend on an average. The coefficients are both statistically and economically significant after controlling for the different external factors (such as the H-Index) and internal factors (such as total assets, firm age, ROA, Tobin's Q, Cash, Leverage ratio, CAPEX, R&D Expenses etc.). The results in Table 3 show that firms experience a substantial drop in innovation after the enactment of SOX in the baseline model.

Although the baseline model on the impact of SOX enactment on innovation effectiveness does highlight the significant negative relationship, we still have to establish the plausible channels for such a decline. Tobin's Q measures the firm's market values with respect to its asset value, and a high Tobin's Q signifies a growth firm rather than a value firm. Table 4 reports the regression results of the impact of SOX on innovation when firms are divided into 2 subsamples according to the median value of the firms' Tobin's Q. The regressions results show that the SOX's impact on patents and innovation efficiency becomes more pronounced in firms with higher Q. This result suggests that SOX stifles innovation in general but the effect is greater for growth firms. For firms that are of higher value, the impact of SOX on innovation is substantially dampened. The result indicates that for growth firms SOX legislation precipitated a nearly 20% drop in patents, while the drop was only 1.5% (statistically insignificant) among the firms with low Tobin's Q (i.e., firms with high growth potential), ceteris paribus. For the innovative efficiency of high Q firms, the SOX legislation caused a statistically significant drop of 6.4 patents per R&D dollar spent. The corresponding drop for low Q firms of 4.7 patents per R&D dollar is statistically insignificant, which we surmise as possibly being due to sampling variation.

Table 5 reports the regression results of the impact of SOX on innovation by dividing firms according to corporate governance quality. We follow Gomperset al.(2003) in dividing firms into 2 subsamples according to the mean value of the G-index. The regressions results show that SOX's impact on patents remains pronounced only for firms with poor corporate governance. According to the G-index which captures shareholder protection, poorer rights protection leads to a bigger drop in patents and innovative efficiency. All else being equal, a poorly governed firm saw a drop in 15.5% patents compared to only 6.9% for a better governed firm. In terms of innovative efficiency, a poorly governed firm had 0.33 fewer patents per dollar of R&D expenses comparing to a 0.03 drop for better governed firms. As expected, SOX did not have a big enough impact statistically for companies with better governance.

We further investigate the impact of SOX on firms operating in the high-tech industries as opposed to the non-high-tech industries. This helps us to understand the impact of the SOX legislation by controlling for the innovativeness of the industry. There are two main issues. First, the aftermath of the tech sector bubble's bursting, which occurred in 2000-2001. Second, the ease of innovating or patenting in these two types of sector are inherently different and might have had a differential impact of SOX. We split the sample into two subsamples and report the regression results in Table 6. The coefficient of SOX dummy on log of patents is significant and negative in both subsamples but is significantly greater in magnitude for high-tech industries. On the other hand, the impact of SOX on innovation efficiency only remains statistically significant and negative for firms in high-tech sectors but becomes insignificant in the low-tech industries. A high-tech firm had a drop in productivity in patents of 15% compared to the non-tech firms registering a drop in 3.5% controlling for other factors. We further report a 0.055 drop in the number of patents filed per R&D dollars spent after accommodating for depreciation and controlling for other factors. In sum, we can say that firms in the high-tech industry did indeed play a role in the reduction in innovation and innovative effectiveness as an aftermath of SOX, but only part of it can be explained by the funding crunch in the aftershock of the tech-sector bubble.

The nature of the decline in innovation and its causes could potentially also result from the actions of those companies which actively delisted during and after the SOX legislation. The main thrust of the argument is that companies which found it difficult to be sustainable in a post-SOX regime actively sourced for funds to go private to avoid the cost of compliance and additional supervision enactment of SOX entails. However, such an analysis of private firms is not without its own shortcomings. One potential concern about our results are the omitted variables in the regressions, since the SOX will affect many corporate behaviors that may not be captured in the regressions. We therefore utilize a set of firms that delisted at the time of the SOX legislation, and compare the impact of SOX on delisted firms as opposed to those that remained listed. The results are reported in Table 7.

The regression in Table 7 includes the post-SOX dummy, the delisting dummy, their interaction term and the control variables used in other tables. The coefficient on the delisting dummy is negative and significant, hence controlling the impact of delisting directly. The post-SOX dummy is significant and negative, suggesting that the SOX legislation causes firms to innovate less. The interaction term between SOX dummy and delisting dummy is positive and significant, suggesting that firms which delisted are less adversely affected by the SOX legislation than firms that remained public. The results also stay the same even when we do not control for any of the standard covariates (Table 7 Panel (1)). Our findings in Table 7 confirm the negative impact of SOX on innovation, and our findings are not caused by endogeneity (or selection) concerns such as an omitted variable bias. Summing up, SOX had a significant negative impact on innovation, but this result is not driven by firms delisting alone. In fact, the firms that stay public seems to be less innovative after implementation of SOX.

Chapter 5 Possible Managerial Mechanisms Underlying SOX's Effects on Innovative Performance

The public need for SOX notwithstanding, our findings offer evidence that such regulations are having perverse effects on firms' innovative behavior, and presumably, on their eventual competitiveness. We have yet to suggest a reasonable managerial model or process by which these impacts may happen. That SOX simply clamped down on managerial indiscretion by itself may not directly translate to a lower propensity to innovate, though by requiring independent oversight and its other provisions, SOX has been said to constrain managers' risk-taking (Bargeron et al., 2010). To further understand the effect of SOX on innovation, we examine how regulatory mechanisms may yield unintended consequences by their influence on managerial decision-making.[22] To reiterate observations from the earlier literature, while regulations have historically already been seen to have had negative side effects through direct costs of compliance (Hahn 1998; Hahn and Hird, 1991), they have also had unintended consequences. While there is evidence on SOX's effect on certain other decisions such as public listings, this is also the result of direct impacts (on costs).

It is worth nothing that the corporate governance literature itself is strongly defined by the notion of "misconduct" and its "appropriate" governance. Governance is complicated by multidisciplinary facets (Aguilera and Jackson, 2010), and misconduct itself has been attributed to a plethora of possible

[22]While anecdotal evidence surfaced on concerns that SOX was having unnecessarily negative effects, understanding of its potential effects on innovation took longer to gestate. On top of this, academia was generally recognized to be lagging behind practice in understanding the negative effects, including at the time of SOX (Aguilera and Cuervo-Cazurra, 2009).

underlying reasons (Greve et al., 2010).[23] It is also known that individual traits and behaviors can interact with organizational incentives and expectations in more complex ways than straightforward economic self-interest would presume (Mishina et al., 2005). However, there is also an expanse of corporate behavior that is not purely in the realm of misconduct, but that is instead 'rational conduct'. In some of these cases, with SOX, a 'well-intentioned regulation, bad side effect' mechanism may be at work.

Since regulations, and SOX in particular, can affect the propensity to take risks, (Bargeron et al., 2010; Fama, 1980), our findings on higher growth firms and high tech firms (which are the typically ones taking on more risks), suggests a possible regulatory-induced bias against risk-taking – both proper (risks) and otherwise. It is known for instance that the more "sustaining" innovations are by definition not "disruptive", and hence, associated with less risky investments (Christensen and Bower, 1996), and presumably, faster growing and innovative firms such as start-ups. SOX also enhances the pathways for exercising responsible behavior creates as well as increases the penalties on managers. This intended effect appears to be working, given our results showing that the well-governed firms suffer less adverse effects on their patenting. Those with weaker governance processes or regimes may have higher than acceptable risk profiles (i.e. may be undertaking "risky" innovations), and so (appropriately) have their propensity to innovate decreased by SOX.

[23] Reasons traditionally cited as underlying CEO misconduct include organizational culture, cognitive biases, ethical decision-making processes, hubris (which has an aspect of behavioral bias but also personality traits), willful blindness (partly based on cognitive inabilities of seeing one's acts from other perspectives) (Greve et al., 2010; Hefferman, 2011), as well as rationally-governed misconduct (i.e., the self-interested nature of the economic paradigm) as taught in theories of business (Pfeffer, 2005).

We next examine the interaction of regulations with *appropriate but risky* corporate behavior by way of simple cognitive models of decision-making. Instead of simply restricting firms' behavior as command and control regulations did, SOX provided for greater accountability and independent oversight by treating the corporation as a system of activities and stakeholders, and seeking to enhance accountability through increased transparency (via audit trails) and shifting the balance of power (by way of independent directors). In this way, SOX can be seen to be following well-established findings showing that independent boards act as controls on corporate excesses (Fama, 1980; Fama and Jensen, 1983; Pozner, 2007). Since managerial discretion enhances the positive relationship between traits as CEO hubris and firm risk-taking (Li and Tang, 2010),by increasing external monitoring and clamping down on such managerial indiscretion, SOX can be said to be seeking to control such behavior and conditions by promoting "low-discretion" environments (Hambrick and Finkelstein, 1987; Peteraf and Reed, 2007). In general, hubristic CEOs (which are not a small proportion of the population) will exercise strong control over innovation, but this effect is weakened when task complexity increases (Tang et al., 2012). Regulations may very well add to that task complexity, weakening that strong control (Hahn, 1998),this being quite in-line with bounded rationality assumptions on decision-making.

With regards to the classical innovation activities of R&D and new product development, the manager's decision problem consists of creating and deciding from amongst a feasible set of strategic choices within the firm. This is often typically described as creating a "funnel" of project ideas which are winnowed out over time. The question is: how are regulations acting on managers' mindsets and shaping (or restricting) such actions? The decision to pursue a particular innovative product (or service) or the project leading up to it (including the scientific or technical research) is often made using rational calculi, weighing the benefits and likelihoods of technical and market success.[24] Much of what firms already do in the way of making technology decisions involves mitigating the risks of product and investment decisions, and thereby reducing the uncertainty in facing them.[25] The resulting set of "investment options" would largely consist of what remains feasible technologically, financially and strategically. Regulations that increase the risks of taking certain technological choices (say by suggesting new levels of risks that could be penalized), can act as further constraints on the set of viable choices or range of permissible actions. In addition to this, technological choices nowadays (but especially just before 2000) are associated with (that is, enacted by) new business models, some of which incorporate different economic arrangements with external parties (Osterwalder and Pigneur, 2010; Teece, 2010; Zott and Amit, 2008), but which may also entail different types of risks (risks of diversifying or moving beyond stakeholders' understandings and expectations being a simple example). Thus, what on the surface appears to be a technological investment decision may actually be associated with a particular business model predicated on extracting value from

[24]The stage gate process exemplifies this, using certain stages of the product development process as cut off points at which projects are allowed to proceed or to be halted (Krishnan and Ulrich, 2001; Ulrich and Eppinger, 1995).

[25]Firms employ means such as cross-functional and cross-level teams to increase the different views on a problem or solution, technology scanning and other predictive methods (Brown and Eisenhardt, 1997; Calantone et al., 2003), and shortening the product cycle in order to increase information (Krishnan and Bhattacharya, 2002).

external partnerships – one that may be deemed riskier (at risk of being penalized) under the new regulatory regime.[26]

As regulations shape choices within an industry, through firms' mimetic behavior or other "coerced" means (e.g. consultants indicating the new risks and penalties across their clients), they can become embedded as new "industry recipes" that further act to sanction or otherwise limit the set of actions deemed permissible to the entire industry (Peteraf and Reed, 2007; Spender, 1989). These are just some of the pathways by which regulations may impact on the innovative behaviors and underlying decision-making of firms. More detailed research could be warranted to test whether some of these pathways have clearer or stronger effects than others.

[26]Presumably then, some risky technologies require more creative engagements with external parties and parts of the value chain. Tesla's branching into charging stations (creating its own value chain) is an example integrating new technology with a new business model. In general, the concept of innovation is itself considered by some to be expanding to recognize its effects and desired properties of helping firms bridge and capture value *across* established industry boundaries (Hacklin, 2007), and when modern entrepreneurial thought promotes firms having an even freer hand to innovate, to experiment and even to fail(Blank, 2013).

Chapter 6 Conclusion

The question more informed regulators would like to ask is, how can regulations such as SOX isolate problems and implement appropriate mechanisms and incentives in order to correct for these individual and systemic failures without jeopardizing corporate performance? While this cannot be easily answered, we can shed light on the conditions and means by which such failures can occur. In the research, we directly examine the hypothesis that SOX stifles corporate innovation. We provide direct evidence for the first time in the literature that such impacts exist. For example, for US listed firms in 4 years after the enactment of the SOX, they experience a significant drop in innovation.

We show that the impact of SOX on innovation have an interesting cross-sectional pattern. Growth firms especially those with above average growth opportunities experience greater drop in innovation. Similarly, SOX's impact on innovation is more pronounced in firms operating in high-tech industries or firms with poor corporate governance, consistent with the regulatory purpose of raising compliance costs particularly for these "riskier" firms. Finally, we show that the impact of SOX on innovation is not solely driven by its status of being publicly listed since no such effect is found in firms gone private before SOX.

Our research shows that policies that aim to impact on corporations universally may still have unintended consequences. This has important implications for policy makers, particularly ones interested in the competitiveness implications of any regulations.

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Appendices

Appendix A Tables for Part I

Appendix Table I.A
Variable Definitions

Variable	Definition
Innovation measures	
Ln(1+Patent)	Natural logarithm of one plus the patent number. Patent number is defined as number of patent applications filed in year *t* of each firm. Only patents that are later granted are included. The patent number is set to zero for companies that have no patent information available from the NBER database.
Ln(1+Citation)	Natural logarithm of one plus the citation number. Citation number is defined as number of citations received by patent applications filed in year *t* of each firm. The citation number is corrected for the truncation bias in citation counts using the Hall, Jaffe, and Trajtenberg (2001) adjustment factor. Only patents that are later granted are included. The citation number is set to zero for companies that have no citation information available from the NBER database.
Ln(1+Generality)	Natural logarithm of one plus the generality scores. Generality score is defined as one minus the Herfindahl index of the three-digit technology class distribution of all the patents that cite a given patent. We then take the sum for all patent applications filed in year t of each firm. Only patents that are later granted are included. For firms that generate no patents in a year, their patents generality scores are undefined and therefore treated as missing.
Ln(1+Originality)	Natural logarithm of one plus the originality scores. Originality score is defined as one minus the Herfindahl index of the three-digit technology class distribution of all the patens that a given patent cites. We then take the sum for all patent applications filed in year *t* of each firm. Only patents that are later granted are included. For firms that generate no patents in a year, their patents orginality scores are undefined and therefore treated as missing.
Real estate value and price index	
Ln(1+RE Value) (MSA)	Logarithm of one plus the market value of real estate assets using the Metropolitan Statistical Area (MSA)-level real estate price index divided by the lagged PPE (PPENT from COMUSTAT) in year *t* of each firm. Detailed description on the calculation of the market value of real estate assets is provided in the Internet Appendix.
Ln(1+RE Value) (State)	Logarithm of one plus the market value of real estate assets using the state-level real estate price index divided by lagged PPE in year *t* of each firm.
Real Estate Price Index (MSA)	Home Price Index (HPI) at the MSA level in year *t* of each firm, a broad measure of the movement of single family home prices in the United

	States, provided by the Office of Federal Housing Enterprise Oversight (OFHEO).
Real Estate Price Index (State)	Home Price Index (HPI) at the state level in year t of each firm, a broad measure of the movement of single family home prices in the United States, provided by the Office of Federal Housing Enterprise Oversight (OFHEO).
Control variables	
Ln(Asset)	Firm's total asset. It is defined as logarithm of the book value of total assets (AT from COMPUSTAT) measured at the end of fiscal year *t*.
Ln(1+Age)	Firm's age. It is defined as logarithm of one plus the number of years of the corporation has existed from the IPO year to year *t*.
ROA	Firm's return-on-asset ratio. It is defined as operating income before depreciation (OIBDP from COMUSTAT) divided by book value of total asset (AT), measured at the end of fiscal year *t*.
Tobin's Q	Firm's market-to-book ratio. It is defined as [the market value of equity (PRCC_F×CSHO from COMUSTAT) plus book value of assets (AT) minus book value of equity (CEQ from COMUSTAT) minus balance sheet deferred taxes (TXDB from COMUSTAT)] divided by book value of asset (AT), measured at the end of fiscal year *t*.
Cash	Firm's cash flows. It is defined as income before extraordinary items (IB from COMUSTAT) plus depreciation and amortization (DP from COMUSTAT) divided by lagged PPE (PPENT from COMUSTAT), measured at the end of fiscal year *t*.
Leverage	Firm's leverage ratio. It is defined as book value of debt (DLTT+DLC from COMUSTAT) divided by book value of total assets (AT) measured at the end of fiscal year *t*.
R&D Expense	Firm's research and development expenditure. It is defined as research and develop expenditure (XRD from COMUSTAT) divided by book value of lagged PPE (PPENT), measured at the end of fiscal year *t*.
CAPX	Firm's capital expenditure. It is defined as capital expenditure (CAPX from COMUSTAT) divided by book value of lagged PPE (PPENT), measured at the end of fiscal year *t*.
Herfindahl Index	Herfindahl index of 3-digit SIC industry of each firm measured at the end of fiscal year *t* based on sales.

Appendix Table I.B
Sample Calculations for General Motors (GM) (In millions of dollars)

Step 1: Obtain Age and Purchase Year of Real Estate
Fiscal Year 1993 data:
Property, Plant, and Equipment for Buildings at Cost = $13,577
Accumulated Depreciation for Buildings = $6,889.7
Proportion of Buildings Used = 0.5075
Age = 20
Purchase Year = 1973

Step 2: Estimate Book Value of Real Estate
Book Value of Real Estate in Fiscal Year 1993
= Buildings at Cost + Construction in Progress at Cost + Land and Improvements at Cost
= $18,278

Step 3: Estimate Market Value of Real Estate as of 1993
Market Value of Real Estate as of 1993
= RE Book Value * (HPI_1993/HPI_1975)*(CPI_1975/HPI_1973)
=$58,943

Step 4: Estimate Impact of Real Estate Shocks on Market Value of Real Estate from 1993 to

Step 5: Calculate the RE Value Ratio
RE Value in Year *t* = (Market Value of Real Estate in Year *t*)/(PPE in Year *t*-1)

Year	RE Market Value in 1993	MSA-level Price Index	RE Market Value	Lagged PPE	RE Value
1993	58,943	0.511	58,943	46,777	1.26
1994	58,943	0.536	61,827	47,320	1.31
1995	58,943	0.573	66,094	54,842	1.21
1996	58,943	0.619	71,400	65,442	1.09
1997	58,943	0.666	76,822	67,616	1.14
1998	58,943	0.708	81,666	67,869	1.20
1999	58,943	0.755	87,088	71,514	1.22
2000	58,943	0.809	93,317	76,116	1.23
2001	58,943	0.858	98,969	77,843	1.27
2002	58,943	0.896	103,352	73,738	1.40
2003	58,943	0.926	106,812	72,784	1.47
2004	58,943	0.946	109,119	72,594	1.50

Table I.1
Summary Statistics

This table reports descriptive statistics for the sample of firms with real estate data from 1993 to 2004. Columns (1) to (6) report the mean, standard deviation (S.D.), 25th percentile (P25), median, 75th percentile (P75), and the number of observations of each variable (N), respectively, for the full sample of 26,083 firm-year observations. Columns (7) and (8) report the mean of each variable for the subsamples of firms with high and low real estate collateral value (RE value), respectively. In each year, a high RE value firm is one whose RE value is above the median of RE value based on the Metropolitan Statistical Area (MSA)-level real estate prices, while a low RE value firm is one with below-median RE value. Detailed definitions of each variable are provided in the Appendix.

	Full Sample (N=26,083)						High RE Value (N=13,081)	Low RE Value (N=13,002)
	Mean	S.D.	P25	Median	P75	N	Mean	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Innovation productivity measures								
Patent Number	4.02	14.74	0.00	0.00	1.00	26,083	6.66	1.58
Citation Number	36.17	112.82	0.00	0.00	0.00	26,083	53.08	20.6
Generality	1.00	5.74	0.00	0.00	0.00	26,083	1.71	0.36
Originality	2.00	10.26	0.00	0.00	0.00	26,083	3.45	0.67
Panel B: Real estate value and price index								
Real Estate Value (MSA)	0.80	1.28	0.00	0.23	1.07	24,999	1.58	0.02
Real Estate Price (MSA)	0.54	0.17	0.39	0.52	0.66	25,022	0.58	0.51
Real Estate Value (State)	0.82	1.3	0.00	0.27	1.09	26,083	1.58	0.11
Real Estate Price (State)	0.55	0.16	0.42	0.53	0.66	26,083	0.58	0.52
Panel C: Control variables								
Total Assets	672.3	1,554	18.82	89.48	492.7	26,071	1,113	266.4
Firm Age	17.68	11.67	9.00	14.00	26.00	26,083	23.37	12.45
ROA	0.01	0.24	-0.05	0.06	0.12	25,937	0.07	-0.09
Tobin's Q	2.12	1.59	1.08	1.51	2.47	23,288	1.66	2.54
Cash	0.02	1.48	-0.13	0.24	0.57	25,957	0.21	-1.01
Leverage	0.24	0.22	0.03	0.20	0.37	25,995	0.28	0.21
R&D Expense	0.64	1.29	0.00	0.01	0.51	26,059	0.13	1.11
CAPX	0.37	0.55	0.11	0.21	0.41	26,083	0.22	0.51
Herfindahl Index	0.15	0.11	0.06	0.12	0.20	26,059	0.17	0.13

Table I.2
Real Estate Collateral and Innovation: Patents and Patent Citations

This table reports the OLS estimation results of the baseline panel regressions examining the effects of real estate collateral on innovation productivity from 1993 to 2004. The dependent variables in Columns (1) to (4) are *Ln(1+Patent)*, the logarithm of one plus the number of successful patent applications filed in each year of each firm. The dependent variable in Columns (5) to (6) are *Ln(1+Citation)*, the logarithm of one plus the number of citations received by patents filed in each year of each firm. The main independent variable is *Ln(1+RE Value)*, the logarithm of one plus the market value of real estate collateral normalized by lagged PPE. *RE Value* in Columns (1) to (2) are measured using the state-level real estate prices (*RE Price*), while *RE Value* in Columns (3) to (6) are based on MSA-level *RE Price*. All regressions, except Columns (1), (3), and (5), control for the logarithm of total asset, logarithm of one plus firm age, return on asset (ROA), Tobin's Q, leverage, R&D expense, capital expenditure (CAPX), Herfindahl Index based on the three-digit SIC code, as well as year, two-digit SIC industry, and the MSA of location fixed effects. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the MSA and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Ln(1+Patent)				Ln(1+Citation)	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(1+RE Value) (MSA)			0.324***	0.091***	0.441***	0.121***
			(20.03)	(7.51)	(16.54)	(5.37)
RE Price (MSA)			0.683***	0.207	0.976***	0.189
			(3.68)	(1.64)	(3.13)	(0.84)
Ln(1+RE Value) (State)	0.314***	0.085***				
	(19.90)	(7.20)				
RE Price (State)	-0.232	0.009				
	(-0.81)	(0.04)				
Ln(Asset)		0.277***		0.276***		0.441***
		(45.85)		(44.93)		(39.05)
Ln(1+Age)		0.146***		0.146***		0.197***
		(11.88)		(11.54)		(8.13)
ROA		-0.470***		-0.476***		-0.769***
		(-13.48)		(-13.54)		(-10.17)
Tobin's Q		0.061***		0.062***		0.109***
		(13.17)		(13.22)		(12.78)
Cash		0.011***		0.011***		0.023***
		(4.24)		(4.26)		(3.96)
Leverage		-0.267***		-0.283***		-0.631***
		(-10.96)		(-11.37)		(-13.21)
R&D Expense		0.020***		0.021***		0.082***
		(4.30)		(4.30)		(7.78)
CAPX		-0.026***		-0.025**		-0.029
		(-2.61)		(-2.54)		(-1.28)
Herfindahl Index		0.180**		0.206***		0.366***
		(2.41)		(2.70)		(2.93)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.193	0.415	0.195	0.414	0.194	0.366
Observations	25,809	22,845	24,999	22,146	24,999	22,146

Table I.3

Alternative Measures of Innovation Productivity: Patent Generality and Originality

This table reports the OLS estimation results of the baseline panel regressions examining the effects of real estate collateral on alternative measures for innovation productivity from 1993 to 2004. The dependent variables of Columns (1) to (2) are *Ln(1+Generality)*, the logarithm of one plus the sum of generality scores of all successful patent applications filed in each year of each firm. The dependent variable of Columns (3) to (4) are *Ln(1+Originality)*, the logarithm of one plus the sum of originality scores of all successful patent applications filed in each year of each firm. The main independent variable is *Ln(1+RE Value)*, the logarithm of one plus the market value of real estate assets based on the MSA-level real estate price index normalized by lagged PPE. The regressions control for firm characteristics as well as the year, two-digit SIC industry, and the MSA of location fixed effects. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the MSA and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Ln(1+Generality)		Ln(1+Originality)	
	(1)	(2)	(3)	(4)
Ln(1+RE Value)	0.166*** (14.44)	0.046*** (6.06)	0.252*** (19.16)	0.070*** (7.49)
RE Price	0.251** (2.49)	0.037 (0.49)	0.527*** (3.57)	0.182* (1.84)
Ln(Asset)		0.127*** (21.16)		0.197*** (36.31)
Ln(1+Age)		0.083*** (10.62)		0.110*** (11.90)
ROA		-0.181*** (-8.39)		-0.324*** (-12.89)
Tobin's Q		0.028*** (9.25)		0.045*** (12.24)
Cash		0.002 (1.39)		0.008*** (4.26)
Leverage		-0.131*** (-8.95)		-0.168*** (-9.35)
R&D Expense		0.004 (1.42)		0.000 (0.02)
CAPX		-0.002 (-0.39)		-0.016** (-2.27)
Herfindahl Index		0.078 (1.39)		0.183*** (2.85)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Adj. R^2	0.130	0.279	0.156	0.359
Observations	24,999	22,146	24,999	22,146

Test I.4

Instrumental Variable (IV) Approach

This table reports the IV regression estimation results examining the causal effects of real estate collateral on innovation productivity from 1993 to 2004. Column (1) reports the first-stage regression with the real estate prices (*RE Price*) at the MSA level as the dependent variable and the interaction of local elasticity of land supply interacted with real mortgage rate as the instrumental variable. Columns (2) to (5) report the results of the second-stage regressions, where the dependent variables are different measures of innovation productivity including patents, patent citations, generality and originality. We calculate the market value of real estate collateral (*RE value*) using the predicted *RE Price* from the first stage. All the regressions control for firm characteristics as well as the year, two-digit SIC industry, and the MSA of location fixed effects. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the MSA and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	First Stage	Second Stage			
	RE Price	Ln(1+Patent)	Ln(1+Citation)	Ln(1+Generality)	Ln(1+Originality)
	(1)	(2)	(3)	(4)	(5)
Elasticity Mortgage Rate	0.028*** (6.32)				
Ln(1+RE Value)		0.068*** (5.17)	0.078*** (3.21)	0.038*** (4.49)	0.056*** (5.56)
RE Price		0.158 (0.88)	0.302 (0.86)	0.061 (0.48)	0.194 (1.40)
Ln(Asset)		0.277*** (41.01)	0.441*** (35.38)	0.129*** (19.51)	0.199*** (33.54)
Ln(1+Age)		0.176*** (13.25)	0.237*** (9.14)	0.101*** (12.78)	0.138*** (14.46)
ROA		-0.471*** (-12.69)	-0.784*** (-9.85)	-0.186*** (-8.05)	-0.328*** (-12.31)
Tobin's Q		0.068*** (13.77)	0.119*** (13.24)	0.031*** (9.59)	0.050*** (12.76)
Cash		0.009*** (3.49)	0.022*** (3.55)	0.001 (0.78)	0.007*** (3.52)
Leverage		-0.323*** (-12.07)	-0.704*** (-13.65)	-0.162*** (-10.23)	-0.203*** (-10.65)
R&D Expense		0.021*** (3.99)	0.082*** (7.33)	0.004 (1.34)	0.000 (0.12)
CAPX		-0.034*** (-3.26)	-0.047** (-1.97)	-0.008 (-1.24)	-0.023*** (-3.05)
Herfindahl Index		0.212*** (2.54)	0.403*** (3.03)	0.073 (1.18)	0.193*** (2.71)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.942	0.416	0.366	0.274	0.354
Observations	1,358	19,460	19,460	19,460	19,460

Test I.5

Determinants of Real Estate Ownership and Innovation

This table reports the estimation results of the two-stage panel regressions controlling for the observable determinants of real estate ownership to investigate the causal effects of real estate collateral on innovation. Column (1) reports the results of first-stage regression analyzing the determination of *RE Ownership*, a dummy indicating whether the firm owns any real estate assets or not, with total asset, age, and ROA, as well as the year, industry, and MSA of location as predictors. Columns (2) to (5) report the results of second-stage regressions. The dependent variables are different measures of innovation productivity including patents, patent citations, generality and originality, and the main explanatory variable is *Ln(1+RE Value)*. The second-state regressions control for the predicted *RE Ownership* from the first stage interacted with *RE Price*, firm characteristics as well as the year, two-digit SIC industry, and the MSA of location fixed effects. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the MSA and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	First Stage	Second Stage			
	RE Ownership	Ln(1+Patent)	Ln(1+Citation)	Ln(1+Generality)	Ln(1+Originality)
	(1)	(2)	(3)	(4)	(5)
Ln(1+RE Value)		0.090*** (7.41)	0.118*** (5.26)	0.045*** (6.17)	0.069*** (7.44)
RE Price		0.694*** (5.04)	1.089*** (4.18)	0.781*** (8.37)	0.586*** (5.55)
RE Ownership (Predicted)		-1.317*** (-5.41)	-2.438*** (-5.93)	-2.006*** (-10.37)	-1.088*** (-5.43)
Ln(Asset)	0.072*** (53.76)	0.317*** (30.06)	0.516*** (30.77)	0.189*** (19.43)	0.231*** (25.24)
Ln(1+Age)	0.179*** (51.88)	0.23*** (10.27)	0.351*** (9.01)	0.213*** (13.49)	0.179*** (10.18)
ROA	0.195*** (17.60)	-0.336*** (-7.60)	-0.47*** (-5.56)	-0.041 (-1.53)	-0.242*** (-7.27)
Tobin's Q		0.061*** (12.92)	0.107*** (12.47)	0.027*** (9.11)	0.044*** (11.97)
Cash		0.011** (2.34)	0.017 (1.72)	0.009*** (3.38)	0.014*** (3.94)
Leverage Ratio		-0.293*** (-11.73)	-0.652*** (-13.6)	-0.139*** (-9.53)	-0.173*** (-9.61)
R&D Expense		0.014*** (2.99)	0.068*** (6.60)	-0.001 (-0.23)	-0.005 (-1.37)
CAPX		-0.026*** (-2.60)	-0.031 (-1.36)	-0.001 (-0.06)	-0.017** (-2.41)
Herfindahl Index		0.229*** (3.04)	0.409*** (3.28)	0.115** (2.15)	0.202*** (3.21)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.530	0.415	0.367	0.288	0.360
Observations	25,937	22,146	22,146	22,146	22,146

Test I.6
Real Estate Purchasers and Innovation

This table reports the estimation results of the subsample regressions examining how the effects of real estate prices on innovation productivity differ across the non-land-purchasers, future purchasers before their real estate acquisition, and purchasers after the acquisition. The innovation measures in dependent variables are the number of successful patent applications and patent citations in each year of each firm. The main independent variable is *RE Price*, the real estate price at the MSA-level. All the regressions control for firm characteristics as well as the year, two-digit SIC industry, and the MSA of location fixed effects. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the MSA and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Ln(1+Patent)			Ln(1+Citation)		
	Non-purchaser	Purchaser before the purchase	Purchaser after the purchase	Non-purchaser	Purchaser before the purchase	Purchaser after the purchase
	(1)	(2)	(3)	(4)	(5)	(6)
RE Price	0.018 (1.18)	0.150 (1.59)	0.658*** (3.73)	-0.09 (-1.10)	0.344 (1.11)	1.012*** (2.81)
Ln(Asset)	0.042*** (31.83)	0.147*** (14.16)	0.236*** (15.15)	0.21*** (30.15)	0.446*** (12.94)	0.375*** (11.79)
Ln(1+Age)	-0.011*** (-3.48)	-0.017 (-0.82)	0.072 (1.55)	-0.069*** (-4.37)	-0.126* (-1.85)	0.179* (1.89)
ROA	-0.072*** (-7.82)	-0.102 (-1.46)	-0.206 (-1.62)	-0.314*** (-6.51)	-0.273 (-1.18)	-0.258 (-0.99)
Tobin's Q	0.013*** (13.98)	0.029*** (4.58)	0.073*** (6.78)	0.071*** (14.79)	0.084*** (4.01)	0.158*** (7.16)
Cash	0.001 (0.46)	-0.019** (-2.15)	0.013 (0.83)	0.007 (1.08)	-0.055* (-1.92)	0.015 (0.46)
Leverage Ratio	-0.075*** (-11.14)	-0.042 (-0.73)	-0.196** (-2.29)	-0.308*** (-8.73)	-0.297 (-1.54)	-0.336** (-1.92)
R&D Expense	0.001** (-2.05)	-0.001 (-1.34)	0.004 (0.87)	0.001 (-1.65)	-0.002 (-1.05)	0.006 (0.63)
CAPX	-0.003 (-1.43)	-0.026* (-1.69)	-0.016 (-0.87)	-0.005 (-0.43)	-0.082* (-1.66)	-0.006 (-0.15)
Herfindahl Index	-0.052** (-2.39)	-0.845*** (-4.98)	-0.514* (-1.84)	-0.269** (-2.38)	-2.838*** (-5.04)	-0.572 (-1.00)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.227	0.369	0.395	0.204	0.311	0.344
Observations	17,378	2,020	1,863	17,378	2,020	1,863

Table I.7
Innovation over Subsequent Years

Panels A to E report the intertemporal effects of real estate collateral at year t on innovation productivity over subsequent years from t+1 to t+5, respectively. The dependent variables are measures of innovation productivity including the number of successful patent applications, patent citations, generality and originality scores in each year of each firm. The main independent variables is *Ln(1+RE Value)*, the logarithm of one plus the market value of real estate assets based on MSA-level real estate price index normalized by lagged PPE. All the regressions control for firm characteristics as well as the year, two-digit SIC industry, and the MSA of location fixed effects as used in Tables 2 and 3, but their coefficients are not reported for brevity. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the MSA and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Ln(1+Patent)	Ln(1+Citation)	Ln(1+Generality)	Ln(1+Originality)
	(1)	(2)	(3)	(4)
Panel A: Innovation over year *t+1* (N=21,454)				
Ln(1+RE Value)	0.111*** (8.89)	0.138*** (5.84)	0.049*** (5.73)	0.081*** (8.45)
Panel B: Innovation over year *t+2* (N=20,727)				
Ln(1+RE Value)	0.109*** (8.16)	0.139*** (5.66)	0.045*** (4.98)	0.077*** (7.57)
Panel C: Innovation over year *t+3* (N=19,956)				
Ln(1+RE Value)	0.099*** (7.15)	0.124*** (4.93)	0.036*** (4.05)	0.069*** (6.44)
Panel D: Innovation over year *t+4* (N=19,119)				
Ln(1+RE Value)	0.087*** (6.22)	0.099*** (4.37)	0.029*** (3.36)	0.060*** (5.57)
Panel E: Innovation over year *t+5* (N=18,215)				
Ln(1+RE Value)	0.069*** (4.98)	0.074*** (3.42)	0.021*** (2.96)	0.043*** (4.58)
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes

Table I.8
Financial Constraint and Innovation

This table reports the estimation results of subsample regressions examining how the effects of real estate collateral on innovation productivity vary with the level of financial constraint. We use the KZ index of Kaplan and Zingales (1997) as a proxy for the extent of financial constraint. In each year, firms with a KZ index above the sample median are considered as financially constrained (Yes); otherwise, they are regarded as unconstrained (No). The dependent variables are measures of innovation productivity including patents, patent citations, generality and originality; the main explanatory variable is *Ln(1+RE Value)*. The regressions also control for firm characteristics as well as the year, two-digit SIC industry, and the MSA of location fixed effects. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the MSA and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Ln(1+Patent)		Ln(1+Citation)		Ln(1+Generality)		Ln(1+Originality)	
	Con.	Unc.	Con.	Unc.	Con.	Unc.	Con.	Unc.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+RE Value)	0.134***	0.027	0.191***	0.025	0.069***	0.009	0.107***	0.017
	(8.05)	(1.40)	(6.52)	(0.70)	(6.92)	(0.70)	(8.42)	(1.12)
RE Price	0.207	0.131	0.240	0.028	-0.022	0.030	0.192	0.098
	(1.62)	(0.78)	(1.04)	(0.09)	(-0.26)	(0.31)	(1.65)	(0.82)
Ln(Asset)	0.224***	0.336***	0.356***	0.537***	0.092***	0.166***	0.156***	0.243***
	(35.50)	(39.34)	(33.80)	(34.93)	(19.50)	(19.40)	(28.20)	(31.77)
Ln(1+Age)	0.093***	0.171***	0.139***	0.208***	0.049***	0.099***	0.065***	0.135***
	(6.07)	(9.87)	(4.74)	(6.22)	(6.19)	(8.38)	(5.97)	(10.53)
ROA	-0.473***	-0.454***	-0.793***	-0.694***	-0.162***	-0.193***	-0.313***	-0.324***
	(-10.26)	(-8.43)	(-7.68)	(-6.61)	(-6.36)	(-5.86)	(-9.40)	(-8.12)
Tobin's Q	0.043***	0.079***	0.092***	0.127***	0.020***	0.034***	0.030***	0.059***
	(7.56)	(10.59)	(8.11)	(9.06)	(6.25)	(6.17)	(6.74)	(9.44)
Cash	0.017***	0.004	0.034***	0.008	0.006***	-0.002	0.011***	0.004
	(5.26)	(1.02)	(4.33)	(0.99)	(3.23)	(-0.69)	(4.97)	(1.58)
Leverage Ratio	-0.183***	-0.041	-0.392***	-0.252**	-0.066***	0.023	-0.104***	0.012
	(-5.20)	(-0.75)	(-5.86)	(-2.38)	(-3.73)	(0.65)	(-4.23)	(0.35)
R&D Expense	0.031***	0.020***	0.091***	0.081***	0.010***	0.001	0.008	0.000
	(4.42)	(2.66)	(5.45)	(5.45)	(2.95)	(0.11)	(1.61)	(0.01)
CAPX	-0.008	-0.028*	-0.005	-0.028	0.005	0.001	-0.001	-0.020*
	(-0.63)	(-1.69)	(-0.17)	(-0.75)	(0.72)	(0.12)	(-0.11)	(-1.67)
Herfindahl Index	0.438***	-0.002	0.636***	0.084	0.135**	0.036	0.317***	0.081
	(4.56)	(-0.02)	(3.82)	(0.46)	(2.19)	(0.44)	(4.06)	(0.89)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.377	0.469	0.329	0.412	0.238	0.330	0.326	0.410
Observations	11,028	11,118	11,028	11,118	11,028	11,118	11,028	11,118

Table I.9
Debt Financing Dependence and Innovation

This table reports the estimation results of the subsample regressions examining how the effects of real estate collateral on innovation productivity vary with the dependence of debt financing. In each year, firms with debt outstanding are considered as debt financing dependent (with) and vice versa. The dependent variables are measures of innovation productivity including patents, patent citations, generality and originality; the main explanatory variable is *Ln(1+RE Value)*. The regressions also control for firm characteristics as well as the year, two-digit SIC industry, and the MSA of location fixed effects. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the MSA and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Ln(1+Patent)		Ln(1+Citation)		Ln(1+Generality)		Ln(1+Originality)	
	With	Without	With	Without	With	Without	With	Without
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+RE Value)	0.093*** (7.04)	0.003 (0.08)	0.116*** (4.76)	0.044 (0.66)	0.051*** (6.16)	-0.011 (-0.68)	0.076*** (7.33)	-0.024 (-1.1)
RE Price	0.207* (1.69)	0.308 (0.97)	0.214 (0.94)	0.222 (0.36)	0.023 (0.28)	0.234 (1.55)	0.182* (1.81)	0.268 (1.21)
Ln(Asset)	0.284*** (47.31)	0.247*** (13.02)	0.447*** (42.21)	0.449*** (13.7)	0.132*** (22.04)	0.100*** (7.76)	0.203*** (37.7)	0.171*** (10.58)
Ln(1+Age)	0.147*** (11.16)	0.069*** (2.70)	0.215*** (8.65)	-0.028 (-0.47)	0.087*** (10.74)	0.000 (0.01)	0.111*** (11.58)	0.048 (2.75)
ROA	-0.511*** (-12.44)	-0.178*** (-2.61)	-0.794*** (-9.37)	-0.230 (-1.35)	-0.247*** (-10.57)	-0.013 (-0.38)	-0.377*** (-12.3)	-0.142*** (-2.99)
Tobin's Q	0.067*** (11.63)	0.043*** (5.14)	0.115*** (11.32)	0.077*** (4.48)	0.032*** (8.76)	0.017*** (3.33)	0.050*** (11.71)	0.030*** (4.33)
Cash	0.016*** (2.80)	-0.004 (-0.47)	0.028** (2.35)	-0.024 (-1.07)	0.014*** (4.25)	-0.007 (-1.57)	0.019*** (4.44)	-0.002 (-0.32)
Leverage Ratio	-0.283*** (-10.86)	-	-0.621*** (-12.53)	-	-0.128*** (-7.94)	-	-0.157*** (-8.16)	-
R&D Expense	0.012** (1.99)	0.041*** (4.84)	0.065*** (5.04)	0.091*** (4.54)	0.001 (0.39)	0.015*** (3.36)	-0.009** (-2.21)	0.023*** (3.76)
CAPX	-0.030*** (-2.69)	-0.032 (-1.62)	-0.069*** (-3.07)	0.038 (0.76)	-0.005 (-0.74)	-0.002 (-0.21)	-0.015* (-1.82)	-0.035*** (-2.71)
Herfindahl Index	0.298*** (3.64)	-0.685*** (-4.61)	0.551*** (4.06)	-1.382*** (-4.08)	0.109* (1.73)	-0.335*** (-4.55)	0.250*** (3.59)	-0.532*** (-5.06)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.4304	0.3363	0.3872	0.2969	0.294	0.2276	0.3751	0.2917
Observations	18,898	3,248	18,898	3,248	18,898	3,248	18,898	3,248

Table I.10
Industries with Different Levels of Innovation Difficulties

This table reports the estimation results of the subsample regressions examining how the effects of real estate collateral on innovation productivity vary with the degree of difficulty in innovation. As in Hall, Jaffe, and Trajtenberg (2005) and Tian and Wang (2011) the hard to innovation industries include pharmaceutical, medical instrumentation, chemicals, computers, communications, and electrical industries, and the rest are classified as easy to innovation industries, which include software programming, internet applications, and other low-tech industries. The dependent variables are measures of innovation productivity including patents, patent citations, generality and originality; the main explanatory variable is *Ln(1+RE Value)*. The regressions also control for firm characteristics as well as the year, two-digit SIC industry, and the MSA of location fixed effects. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the MSA and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Ln(1+Patent)		Ln(1+Citation)		Ln(1+Generality)		Ln(1+Originality)	
	Hard	Easy	Hard	Easy	Hard	Easy	Hard	Easy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+RE Value)	0.152***	0.075***	0.222***	0.096***	0.132***	0.028***	0.139***	0.054***
	(4.18)	(5.34)	(3.36)	(3.76)	(4.27)	(3.4)	(4.64)	(5)
RE Price	0.603***	0.097	1.449***	-0.062	0.544***	-0.028	0.621***	0.084
	(2.91)	(0.78)	(3.69)	(-0.27)	(3.42)	(-0.4)	(3.7)	(0.92)
Ln (Asset)	0.423***	0.241***	0.643***	0.388***	0.216***	0.106***	0.316***	0.169***
	(29.4)	(47.14)	(28.95)	(38.17)	(12.91)	(24.75)	(21.2)	(41.61)
Ln (1+Age)	0.255***	0.143***	0.230***	0.214***	0.198***	0.075***	0.235***	0.099***
	(7.67)	(12.27)	(3.87)	(8.84)	(8.49)	(11.46)	(9.04)	(12.46)
ROA	-0.687***	-0.412***	-1.112***	-0.569***	-0.387***	-0.174***	-0.537***	-0.308***
	(-8.34)	(-10.46)	(-5.91)	(-7.13)	(-6.73)	(-8.51)	(-7.98)	(-11.09)
Tobin's Q	0.074***	0.056***	0.127***	0.102***	0.040***	0.024***	0.060***	0.039***
	(7.17)	(11.43)	(6.63)	(10.93)	(5.88)	(7.97)	(7.81)	(10.12)
Cash	0.021*	0.006	0.054**	0.002	0.018**	0.002	0.023***	0.008**
	(1.76)	(1.25)	(2.02)	(0.18)	(2.46)	(0.87)	(2.58)	(2.12)
Leverage Ratio	-0.349***	-0.268***	-0.762***	-0.601***	-0.146***	-0.121***	-0.217***	-0.158***
	(-4.43)	(-11.53)	(-5.11)	(-12.43)	(-2.92)	(-8.93)	(-3.73)	(-9.54)
R&D Expense	0.031***	0.028***	0.061***	0.113***	0.014**	0.014***	0.008	0.012***
	(2.82)	(4.86)	(2.67)	(8.25)	(2.02)	(4.23)	(1.06)	(2.98)
CAPX	-0.086***	-0.031***	-0.060	-0.061**	-0.013	-0.012**	-0.059***	-0.023***
	(-3.02)	(-2.79)	(-0.97)	(-2.41)	(-0.69)	(-2.06)	(-2.93)	(-3.1)
Herfindahl Index	-2.995***	0.435***	-4.517***	0.726***	-1.674***	0.248***	-2.308***	0.387***
	(-6.76)	(5.39)	(-5.95)	(5.34)	(-5.03)	(4.58)	(-6.21)	(5.94)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.523	0.408	0.429	0.365	0.420	0.271	0.502	0.353
Observations	3,963	17,776	3,963	17,776	3,963	17,776	3,963	17,776

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Table IA I.1
Additional Robustness Tests

This table reports the robustness test. Panel A reports the regressions using alternative definition of innovation measurements as dependent variables. Panel B reports the regressions using alternative measurements of real estate values as main independent variables. Panel C reports subsample analysis by excluding firms with zero patents and citations from 1993 to 2004 or located in Silicon Valley area, and Panel D reports sub-period analysis from 1993 to 1997, 1998 to 2000, and 2001 to 2004. Each regression controls for the logarithm of total asset, logarithm of one plus firm age, return on asset (ROA), Tobin's Q, leverage, R&D expense, capital expenditure (CAPX), Herfindahl Index based on the three-digit SIC code, as well as year, two-digit SIC industry, and the MSA of location fixed effects as used in Tables 2 and 3, but their coefficients are not reported for brevity. Detailed definitions of each variable are provided in the Appendix. Standard errors are clustered at the MSA-year level, and heteroskedasticity-robust t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: Alternative definitions of innovation measurements as dependent variables

A.1: Innovation measures without log-transformation (N=22,146)

	Patent	Citation	Generality	Originality
Ln(1+RE Value)	1.187*** (6.68)	8.030*** (5.83)	0.468*** (5.36)	0.914*** (7.23)

A.2: Natural logarithm of one plus average citations, generality, and originality of each patent of each firm (N=22,146)

	$\text{Ln}(1+\frac{\text{Citation}}{\text{Patent}})$	$\text{Ln}(1+\frac{\text{Generality}}{\text{Patent}})$	$\text{Ln}(1+\frac{\text{Originality}}{\text{Patent}})$
Ln(1+RE Value)	0.043*** (2.98)	0.005*** (3.70)	0.012*** (5.73)

A.3: Innovation dummy (Dummy=1 if innovation measure>0, otherwise 0) (N=22,146)

	Patent Dummy	Citation Dummy
Ln(1+RE Value)	0.031*** (5.34)	0.025*** (4.51)

Panel B: Alternative measurements of real estate value as main independent variables

B.1: Real estate value without log-transformation (N=22,146)

	Ln(1+Patent)	Ln(1+Citation)	Ln(1+Generality)	Ln(1+Originality)
RE Value	0.029*** (6.33)	0.038*** (4.55)	0.016*** (5.49)	0.024*** (6.52)

B.2: Raw market value of real estate assets using MSA-level real estate price without normalization by lagged PPE (Billions of $) (N=22,146)				
Raw RE Value	0.050*** (11.10)	0.070*** (10.62)	0.040*** (7.27)	0.060*** (12.20)
B.3: Logarithm of one plus raw market value of real estate assets using MSA-level real estate price without normalization by lagged PPE (N=22,146)				
Ln(1+Raw RE Value)	0.095*** (14.96)	0.111*** (10.59)	0.063*** (13.61)	0.087*** (16.84)
B.4: Logarithm of one plus the market value of real estate assets based on MSA-level real estate price normalized by lagged total asset (N=22,146)				
Ln(1+$\frac{\text{Raw RE Value}}{\text{Total Asset}}$)	0.110*** (3.81)	0.149*** (3.32)	0.099*** (5.53)	0.103*** (4.53)
B.5: Real estate ownership interacted with MSA-level real estate price, where RE ownership=1 if a firm owns non-zero real estate assets, otherwise equal to 0 (N=22,168)				
RE Ownership ×RE Price	0.223*** (8.56)	0.454*** (8.71)	0.046*** (3.31)	0.103*** (5.65)
Panel C: Sub-sample Analysis				
C.1: Excluding firms with zero patents and citations from 1993 to 2004 (N=11,972)				
	Ln(1+Patent)	Ln(1+Citation)	Ln(1+Generality)	Ln(1+Originality)
Ln(1+RE Value)	0.101*** (4.96)	0.142*** (3.76)	0.101*** (3.21)	0.124*** (4.28)
C.2: Excluding firms located in Silicon Valley area (N=21,247)				
Ln(1+RE Value)	0.090*** (7.72)	0.123*** (5.52)	0.041*** (6.21)	0.066*** (7.50)
Panel D: Sub-period Analysis				
D.1: From year 1993 to 1997 (N=11,413)				
	Ln(1+Patent)	Ln(1+Citation)	Ln(1+Generality)	Ln(1+Originality)
Ln(1+RE Value)	0.084*** (4.39)	0.141*** (3.76)	0.056*** (4.14)	0.058*** (3.95)
D.2: From 1998 to 2000 (N=3,828)				
Ln(1+RE Value)	0.123*** (3.90)	0.153** (2.52)	0.057*** (3.42)	0.088*** (3.70)
D.3: From 2001 to 2004 (N=6,905)				
Ln(1+RE Value)	0.064*** (3.34)	0.053* (1.83)	0.023*** (2.87)	0.060*** (4.19)

Table IA I.2
Cross-sectional Relationship between Real Estate Collateral and Innovation
This table reports the cross-sectional link between the value of real estate collateral and innovation productivity. The observation unit in this analysis is firm. The dependent variables are firm-level innovation productivity measures such as the annual average number of patents successfully filed from 1993 to 2004 of each firm, and the annual average citations, generality, and originality of all successful patent applications filed from 1993 to 2004 of each firm. The main independent variable is *Ln(1+RE Value)*, the firm-level average of logarithm of one plus the market value of real estate assets based on MSA-level real estate price index normalized by lagged PPE. All regressions control for various average firm characteristics as well as two-digit SIC industry and the MSA of location fixed effects. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the MSA and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Ln(1+Patent)	Ln(1+Citation)	Ln(1+Generality)	Ln(1+Originality)
	(1)	(2)	(3)	(4)
Ln(1+RE Value)	0.100***	0.175***	0.056***	0.073***
	(2.88)	(2.87)	(2.70)	(2.68)
RE Price	-0.310	-1.318***	-0.301***	-0.033
	(-1.63)	(-3.94)	(-2.64)	(-0.22)
Ln(Asset)	0.269***	0.446***	0.133***	0.189***
	(28.58)	(26.95)	(23.60)	(25.57)
Ln(1+Age)	0.112***	0.133***	0.042***	0.079***
	(4.75)	(3.22)	(2.98)	(4.29)
ROA	-0.653***	-1.008***	-0.403***	-0.531***
	(-4.17)	(-3.66)	(-4.29)	(-4.31)
Tobin's Q	0.079***	0.147***	0.039***	0.055***
	(5.95)	(6.30)	(4.86)	(5.22)
Cash	0.022	0.053	0.025*	0.026
	(1.02)	(1.40)	(1.91)	(1.57)
Leverage	-0.400***	-0.804***	-0.182***	-0.248***
	(-5.00)	(-5.71)	(-3.79)	(-3.95)
R&D Expense	-0.018	0.033	-0.016	-0.031**
	(-1.07)	(1.14)	(-1.62)	(-2.40)
CAPX	0.055	0.175**	0.037	0.029
	(1.13)	(2.05)	(1.26)	(0.75)
Herfindahl Index	0.260	0.343	0.108	0.232*
	(1.57)	(1.18)	(1.08)	(1.78)
Industry FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Adj. R^2	0.459	0.456	0.338	0.385
Observations	2,884	2,884	2,884	2,884

Table IA I.3

Alternative Measures of Financial Constraint: Debt Rating and Paper Rating

This table reports the estimation results of subsample regressions examining how the effects of real estate collateral on innovation productivity vary with the level of financial constraint using alternative proxies of financial constraint. Panel A classifies Firms as financially constrained if they have debt outstanding that year but their long-term credit ratings are not available or below the investment grade. Panel B classifies firms as financially unconstrained if they have debt outstanding that year but their short-term credit ratings are not available or below the investment grade. The dependent variables are measures of innovation productivity including patents, patent citations, generality and originality; the main explanatory variable is *Ln(1+RE Value).* The regressions also control for firm characteristics as well as the year, two-digit SIC industry, and the MSA of location fixed effects. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the MSA and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Ln(1+Patent)		Ln(1+Citation)		Ln(1+Generality)		Ln(1+Originality)	
	Con.	Unc.	Con.	Unc.	Con.	Unc.	Con.	Unc.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Debt Rating								
Ln(1+RE Value)	0.095***	-0.004	0.126***	-0.015	0.040***	0.056**	0.069***	0.027
	(6.50)	(-0.13)	(4.80)	(-0.23)	(4.71)	(2.01)	(6.05)	(0.85)
RE Price	0.283**	0.082	0.238	0.662	-0.043	0.594***	0.205**	0.157
	(2.46)	(0.28)	(1.07)	(1.27)	(-0.62)	(3.21)	(2.22)	(0.71)
Ln(Asset)	0.236***	0.344***	0.391***	0.537***	0.101***	0.174***	0.159***	0.268***
	(31.32)	(24.34)	(31.55)	(22.61)	(16.09)	(14.09)	(23.92)	(20.72)
Ln(1+Age)	0.074***	0.305***	0.119***	0.306***	0.034***	0.223***	0.048***	0.263***
	(6.77)	(9.90)	(5.21)	(5.12)	(5.83)	(9.66)	(6.36)	(10.96)
ROA	-0.476***	-0.289***	-0.752***	-0.262	-0.201***	-0.136**	-0.325***	-0.294***
	(-12.16)	(-3.44)	(-8.68)	(-1.55)	(-9.57)	(-2.51)	(-11.45)	(-4.35)
Tobin's Q	0.039***	0.055***	0.084***	0.090***	0.021***	0.011*	0.026***	0.039***
	(8.29)	(6.03)	(8.36)	(5.42)	(7.36)	(1.77)	(7.74)	(5.03)
Cash	0.018***	0.000	0.032***	-0.024	0.015***	-0.008	0.019***	0.003
	(3.39)	(-0.04)	(2.66)	(-1.04)	(5.02)	(-1.37)	(5.01)	(0.35)
Leverage Ratio	-0.234***	-0.081	-0.576***	-0.606	-0.086***	-0.152	-0.106***	-0.087
	(-9.71)	(-0.33)	(-11.78)	(-1.59)	(-6.55)	(-0.88)	(-6.31)	(-0.42)
R&D Expense	0.023***	0.007	0.077***	0.066***	0.006*	0.007	0.002	-0.005
	(3.95)	(0.78)	(5.98)	(3.37)	(1.86)	(1.16)	(0.48)	(-0.66)
CAPX	-0.024**	-0.006	-0.067***	0.075	-0.002	0.001	-0.009	-0.018
	(-2.34)	(-0.25)	(-3.01)	(1.35)	(-0.37)	(0.06)	(-1.27)	(-1.01)
Herfindahl Index	0.230***	0.323	0.391***	0.396	0.016	0.378**	0.195***	0.319*
	(2.85)	(1.64)	(2.75)	(1.23)	(0.28)	(2.53)	(2.94)	(1.89)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.373	0.584	0.338	0.485	0.256	0.457	0.322	0.542

Observations	17352	4387	17352	4387	17352	4387	17352	4387

Panel B: Paper Rating

Ln(1+RE Value)	0.094***	-0.001	0.121***	0.020	0.038***	0.038*	0.068***	0.014
	(6.20)	(-0.01)	(4.47)	(0.37)	(4.43)	(1.82)	(5.87)	(0.61)
RE Price	0.345***	-0.235	0.269	0.131	0.019	0.268*	0.276***	-0.121
	(2.63)	(-1.02)	(1.11)	(0.28)	(0.24)	(1.84)	(2.59)	(-0.71)
Ln(Asset)	0.247***	0.344***	0.403***	0.530***	0.107***	0.174***	0.168***	0.265***
	(32.52)	(33.39)	(32.46)	(29.58)	(16.95)	(17.28)	(24.58)	(29.83)
Ln(1+Age)	0.094***	0.311***	0.143***	0.336***	0.051***	0.197***	0.066***	0.257***
	(8.28)	(10.05)	(6.11)	(6.12)	(8.32)	(7.72)	(8.43)	(10.29)
ROA	-0.498***	-0.340***	-0.742***	-0.456***	-0.219***	-0.156***	-0.353***	-0.297***
	(-11.62)	(-4.88)	(-7.85)	(-3.16)	(-9.32)	(-3.46)	(-11.17)	(-5.38)
Tobin's Q	0.043***	0.055***	0.086***	0.098***	0.022***	0.013***	0.029***	0.037***
	(8.59)	(7.20)	(8.32)	(6.48)	(7.05)	(2.69)	(7.84)	(5.89)
Cash	0.019***	-0.003	0.031**	-0.017	0.016***	-0.007	0.020***	0.001
	(3.09)	(-0.36)	(2.36)	(-0.85)	(4.51)	(-1.36)	(4.53)	(0.19)
Leverage Ratio	-0.243***	-0.211***	-0.588***	-0.514***	-0.190***	-0.159***	-0.210***	-0.122***
	(-9.19)	(-2.98)	(-11.25)	(-3.36)	(-5.99)	(-3.00)	(-5.86)	(-3.38)
R&D Expense	0.022***	0.014	0.083***	0.066***	0.009***	0.003	0.001	-0.001
	(3.73)	(1.64)	(6.09)	(3.75)	(2.88)	(0.54)	(0.26)	(-0.08)
CAPX	-0.013	-0.044**	-0.043*	-0.017	0.001	-0.010	-0.002	-0.040**
	(-1.23)	(-2.05)	(-1.87)	(-0.34)	(0.21)	(-0.78)	(-0.3)	(-2.56)
Herfindahl Index	0.259***	0.419**	0.420***	0.688**	0.036	0.375***	0.209***	0.389***
	(3.24)	(2.55)	(2.94)	(2.38)	(0.61)	(3.32)	(3.22)	(2.86)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.392	0.531	0.353	0.443	0.274	0.399	0.343	0.488
Observations	16,428	5,311	16,428	5,311	16,428	5,311	16,428	5,311

Appendix B Tables for Part II

Variable Definitions

Variable	Definition
Innovation measures	
Patent Number	Patent number is defined as number of patent applications filed in year *t* of each firm. Only patents that are later granted are included. The patent number is set to zero for companies that have no patent information available from the NBER database.
Citation Number	Citation number is defined as number of citations received by patent applications filed in year *t* of each firm. The citation number is corrected for the truncation bias in citation counts using the Hall, Jaffe, and Trajtenberg (2001) adjustment factor. Only patents that are later granted are included. The citation number is set to zero for companies that have no citation information available from the NBER database.
Generality	Generality score is defined as one minus the Herfindahl index of the three-digit technology class distribution of all the patents that cite a given patent. We then take the sum for all patent applications filed in year t of each firm. Only patents that are later granted are included. For firms that generate no patents in a year, their patents generality scores are undefined and therefore treated as missing.
Originality	Originality score is defined as one minus the Herfindahl index of the three-digit technology class distribution of all the patens that a given patent cites. We then take the sum for all patent applications filed in year *t* of each firm. Only patents that are later granted are included. For firms that generate no patents in a year, their patents originality scores are undefined and therefore treated as missing.
Innovation Efficiency	Innovative Efficiency (Hirshleifer, Hsu and Li, 2013) is calculated by taking the number of patents of firm *i* applied in year *t* which eventually got granted divided by firm *i*'s cumulative R&D investment in fiscal year ending from year *t*-4 through year *t*:

Control variables	
Ln(Asset)	The logarithm of the book value of total assets (AT from COMPUSTAT) measured at the end of fiscal year *t*.
Firm Age	The number of years from the firm's IPO year to year *t*.
ROA	Firm operating income before depreciation (OIBDP from COMPUSTAT) divided by the book value of total assets (AT), measured at the end of fiscal year *t*.
Tobin's Q	The market value of equity (PRCC_F×CSHO from COMPUSTAT) plus the book value of assets (AT) minus the book value of equity (CEQ from COMPUSTAT) minus balance sheet deferred taxes (TXDB from COMPUSTAT)] divided by the book value of assets (AT), measured at the end of fiscal year *t*.
Cash Flow-to-Assets	Income before extraordinary items (IB from COMPUSTAT) plus depreciation and amortization (DP from COMPUSTAT) divided by the book value of assets (AT), measured at the end of fiscal year *t*.
Leverage	The book value of debt (DLTT+DLC from COMPUSTAT) divided by the book value of total assets (AT) measured at the end of fiscal year *t*.
PPE-to-Assets	The book value of property, plant and equipment (PPENT from COMPUSTAT) divided by the book value of total assets (AT) measured at the end of fiscal year *t*.
R&D Expense-to-Assets	Research and develop expenditure (XRD from COMPUSTAT) divided by the book value of assets (AT), measured at the end of fiscal year *t*.
CAPX-to-Assets	Capital expenditure (CAPX from COMPUSTAT) divided by book value of assets (AT), measured at the end of fiscal year *t*.
Herfindahl Index	Herfindahl index of the 3-digit SIC industry of each firm measured at the end of fiscal year *t* based on sales.

Table II.1ASummary Statistics

This table presents descriptive statistics for the samples of firms with single-class and dual-class shares during the period 1970-2006.Panel A reports summary statistics for the main four measures of firm innovation output. These are Patent Number(the number of patent applications filed in a given year that are eventually granted), Citation Number(the number of citations received for patent applications filed in a given year that are eventually granted), Generality(one minus the Herfindahl index of the three-digit technology class distribution of all the patents that cite the instant patent summed over all patent applications filed during the year by each firm), Originality(one minus the Herfindahl index of the three-digit technology class distribution of all the earlier patents the patent cites summed over all patent applications filed during the year by each firm) and Innovation Efficiency (defined as the number of patent applications filed in a given year that are eventually granted divided by the R&D Expense of previous years). Panel B reports summary statistics for the control variables used in this study: Total Assets, the logarithm of Total Assets, Firm Age, Return on Assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, CAPX-to-Assets, PPE-to-Assets, R&D Expense-to-Assets, and the Herfindahl Index, at the firm-year level. Detailed definitions of each variable are provided in the Appendix. Columns (1) to (4) and (5) to (8) report the number of firm-year observations (Obs), mean, median and standard deviation (S.D.) of the subsample that covers firms with single-class and dual-class shares, respectively. Column (9) reports the difference in means between the two groups. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using robust t-statistics for two-tailed tests.

	Single-Class Firms				Dual-Class Firms				Dual-Class minus Single-Class
	Obs	Mean	Median	S.D.	Obs	Mean	Median	S.D.	Mean-Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Innovation Productivity Measurement									
Patent Number	103476	7.32	0.00	33.60	3423	6.63	0.00	32.87	-0.69***
Citation Number	103476	97.35	0.00	464.41	3423	93.02	0.00	479.75	-4.34**
Generality	32691	6.13	0.73	22.13	1106	3.47	0.57	12.95	-2.66***
Originality	33213	6.96	0.73	26.75	1299	5.61	0.76	21.71	-1.35**
Innovation Efficiency	58401	0.57	0.00	2.47	2011	0.32	0.02	1.05	-0.25***
Panel B: Control Variables									
Ln (Total Assets in $ millions)	98881	4.69	4.49	2.51	3421	5.64	5.67	2.03	0.96***
Firm Age (years)	103476	15.05	11.00	12.50	3423	18.89	16.00	13.41	3.84***
ROA	98881	0.02	0.12	0.43	3421	0.08	0.13	0.30	0.06***
Tobin's Q	98881	2.12	1.25	3.30	3421	1.97	1.34	2.24	-0.15***
Cash Flow/Assets	98881	-0.04	0.08	0.50	3421	0.02	0.08	0.34	0.06***
Leverage	98881	0.25	0.21	0.29	3421	0.24	0.21	0.22	-0.01***
CAPX/Assets	98881	0.06	0.05	0.06	3421	0.06	0.04	0.05	0.00***
PPE/Assets	98881	0.27	0.22	0.21	3423	0.27	0.24	0.18	0.00
R&D Expense/Assets	98881	0.07	0.02	0.16	3421	0.05	0.01	0.12	-0.03***
Herfindahl Index	103473	0.17	0.13	0.14	3423	0.19	0.16	0.16	0.02***

Table II.1B Summary Statistics

This table presents summary statistics of differences in innovation production between firms with single-class shares and those with dual-class shares. Columns (1) to (4) and (5) to (8) report the numbers of firm-year observations (Obs) and means of the innovation production for the firm-year observations of single-class firms and dual-class firms, respectively. Panel A reports the mean differences in innovation output between firms that are Old (Age above median) and those that are Young (Age below median).Panel B reports the mean differences in innovation output between firms with above median and below median Tobin's Q. Panel C reports the mean differences in innovation output between firms with above median and below median financial constraints as measured by the KZ index. Panel D reports the mean differences in innovation output between firms within Hard-to-Innovate industries and other industries (Easy-to-Innovate). Panel E reports the mean differences in innovation output between firms within High-Technology industries and other industries.***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests.

	Single-Class Firms				Dual-Class Firms					Dual-Class minus Single-Class	
	Obs	Mean	Obs	Mean	Obs	Mean		Obs	Mean	Mean-Difference	
	(1)	(2)	(5)	(6)	(5)	(6)		(7)	(8)	(9)	(10)
Panel A: Age											
	Young		Old		Young			Old		Young	Old
Patent Number	48582	3.09	54894	11.05	1366	4.29		2057	8.18	1.19**	-2.88***
Citation Number	48582	44.17	54894	144.43	1366	54.61		2057	118.53	10.44	-25.90**
Generality	12361	2.48	20330	8.35	373	1.91		733	4.27	-0.57	-4.08***
Originality	13108	3.34	20105	9.32	442	4.49		857	6.19	1.15	-3.13***
Innovation Eff.	22077	0.76	36324	0.45	664	0.53	0	1347	0.21	-0.24*	-0.24***
Panel B: Tobin's Q											
	Low		High		Low			High		Low	High
Patent Number	53465	6.84	50011	7.83	1650	5.69		1773	7.50	-1.15	-0.33
Citation Number	53465	86.18	50011	109.30	1650	75.15		1773	109.65	-11.03	0.35
Generality	15701	6.30	16990	5.98	538	2.76		568	4.15	-3.53***	-1.83**
Originality	16038	7.26	17175	6.68	623	4.54		676	6.59	-2.71**	-0.09
Innovation Eff.	27359	0.53	31042	0.60	1012	0.26		999	0.37	-0.27***	-0.23***
Panel C: Financial Constraint											
	Low		High		Low			High		Low	High
Patent Number	53996	8.43	49480	6.10	1668	7.10		1755	6.18	-1.34	0.08
Citation Number	53996	114.31	49480	78.86	1668	101.03		1755	85.41	-13.28	6.55
Generality	18640	6.58	14051	5.54	579	3.80		527	3.12	-2.78***	-2.42**
Originality	18740	6.95	14473	6.97	679	5.66		620	5.55	-1.29	-1.42
Innovation Eff.	30397	0.56	28004	0.58	1020	0.35		991	0.29	-0.22***	-0.29***
Panel D: Innovation Difficulty											
	Easy		Hard		Easy			Hard		Easy	Hard
Patent Number	80942	6.26	22534	11.10	2674	4.18		749	15.36	-2.08***	4.26***
Citation Number	80942	80.12	22534	159.27	2674	59.59		749	212.36	-20.53***	53.10**
Generality	24177	5.55	8514	7.79	793	2.34		313	6.34	-3.21***	-1.45
Originality	23854	6.14	9359	9.03	936	3.57		363	10.87	-2.58***	1.85
Innovation Eff.	42111	0.63	16290	0.42	1424	0.30		587	0.35	-0.32***	-0.07
Panel E: High-Tech Industries											
	Non		High		Non			High		Non	High
Patent Number	68463	6.39	35013	9.13	2467	3.79		956	13.94	-2.60***	4.81***
Citation Number	68463	77.89	35013	135.41	2467	56.14		956	188.19	-21.75***	52.77***
Generality	19413	6.03	13278	6.28	704	2.33		402	5.48	-3.70***	-0.80
Originality	18870	6.68	14343	7.32	844	3.31		455	9.87	-3.36***	2.54*
Innovation Eff.	32810	0.63	25591	0.49	1237	0.28		774	0.37	-0.35***	-0.12

Table II.2

Innovation Productivity and Share Class Structure

This table reports the estimation results of panel regressions examining the effects of dual-class shares on innovation productivity for the period from 1970 through 2006. The dependent variables in Columns (1) to (4) are the Patent Number(the number of patent applications filed in a given year that are eventually granted), Citation Number(the number of citations received for patent applications filed in a given year that are eventually granted), Generality(the sum of generality scores of all successful patent applications filed by a firm in each year), and Originality(the sum of originality scores of all successful patent applications filed by a firm in each year). The main independent variable is Dual-Class, which equals one if the firm has dual-class shares in year t and zero otherwise. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, R&D Expense-to-Assets, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl Index based on the three-digit SIC code, as well as year and two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

	Patent Number (1)	Citation Number (2)	Generality (3)	Originality (4)
Dual-Class	-5.279***	-62.090***	-3.667***	-3.615***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Total Assets)	6.495***	83.174***	5.210***	5.796***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	0.151***	1.800***	0.004	0.054***
	(0.000)	(0.000)	(0.731)	(0.000)
ROA	-6.984***	-76.258***	-9.211***	-10.249***
	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	0.423***	7.138***	0.069	0.230***
	(0.000)	(0.000)	(0.128)	(0.000)
Cash Flow/Assets	2.004***	20.699**	3.845***	4.740***
	(0.001)	(0.011)	(0.000)	(0.000)
Leverage	-0.467	-13.921***	-0.620	-0.263
	(0.220)	(0.009)	(0.274)	(0.671)
CAPX/Assets	28.153***	469.436***	30.354***	29.980***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D Exp./Assets	8.798***	146.241***	11.678***	10.156***
	(0.000)	(0.000)	(0.000)	(0.000)
PPE/Assets	-7.464***	-125.983***	-7.902***	-7.185***
	(0.000)	(0.000)	(0.000)	(0.000)
Herfindahl Index	6.769***	35.207***	2.215**	0.934
	(0.000)	(0.001)	(0.020)	(0.416)
Constant	-30.907***	-422.962***	-36.289***	-50.688***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	102302	102302	32708	33444
Adj. R^2	0.193	0.169	0.230	0.214
Year F. E.	Yes	Yes	Yes	Yes
Industry F. E.	Yes	Yes	Yes	Yes

Table II.3
Dual-Class Shares, Firm Age, and Innovation

This table reports the estimation results of regressions designed to measure the effect of dual-class shares on innovation productivity for firms of different ages. We regress firm innovation output in year *t* on a Dual-Class dummy variable that equals one if a firm has dual-class shares in year *t* and zero otherwise, and the product of the Dual-Class dummy variable with Firm Age for each firm in each year. The dependent variables are the measures of innovation productivity: Patent Number, Citation Number, Generality, and Originality. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, R&D Expense-to-Assets, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl Index based on the three-digit SIC code, as well as year and two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

	Patent Number (1)	Citation Number (2)	Generality (3)	Originality (4)
Dual-Class	-3.377***	-54.844***	-3.936***	-3.199**
	(0.000)	(0.000)	(0.000)	(0.013)
Dual-Class*Firm Age	-0.082*	-0.108	0.026	-0.019
	(0.089)	(0.875)	(0.630)	(0.758)
Ln(Total Assets)	6.604***	85.615***	5.078***	5.684***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	0.197***	2.466***	0.041***	0.095***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-7.743***	-89.461***	-9.931***	-11.279***
	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	0.419***	6.926***	0.068	0.228***
	(0.000)	(0.000)	(0.123)	(0.000)
Cash Flow/Assets	2.152***	22.501***	3.976***	5.234***
	(0.000)	(0.005)	(0.000)	(0.000)
Leverage	-0.281	-9.639*	-0.574	-0.149
	(0.455)	(0.068)	(0.303)	(0.808)
CAPX/Assets	18.021***	314.647***	19.549***	17.564***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D Exp./Assets	6.863***	111.110***	9.562***	8.408***
	(0.000)	(0.000)	(0.000)	(0.000)
PPE/Assets	-2.561***	-53.348***	-2.520**	-1.017
	(0.001)	(0.000)	(0.014)	(0.406)
Herfindahl Index	3.755***	27.178	2.370	-1.311
	(0.002)	(0.117)	(0.144)	(0.526)
Constant	-28.157***	-354.437***	-33.805***	-47.791***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	102302	102302	32708	33444
Adj. R^2	0.228	0.201	0.279	0.254
Year F. E.	Yes	Yes	Yes	Yes
Industry F. E.	Yes	Yes	Yes	Yes

Table II.4
Dual-Class Shares, Firm Growth Opportunities, and Innovation

This table reports the estimation results of regressions designed to measure the effect of dual-class shares on innovation productivity for firms with different growth opportunities. We regress firm innovation output in year *t* on a Dual-Class dummy variable that equals one if a firm has dual-class shares in year *t* and zero otherwise, and the product of the Dual-Class dummy variable with firm Tobin's Q for each firm in each year. The dependent variables are the measures of innovation productivity: Patent Number, Citation Number, Generality, and Originality. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, R&D Expense-to-Assets, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl Index based on the three-digit SIC code, as well as year and two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

	Patent Number	Citation Number	Generality	Originality
	(1)	(2)	(3)	(4)
Dual-Class	-9.002***	-113.090***	-4.804***	-6.426***
	(0.000)	(0.000)	(0.000)	(0.000)
Dual-Class*Tobin's Q	2.992***	40.051***	1.334*	2.479***
	(0.000)	(0.000)	(0.080)	(0.006)
Ln(Total Assets)	6.449***	83.037***	4.833***	5.466***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	0.201***	2.638***	0.038***	0.094***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-7.519***	-85.436***	-8.337***	-9.891***
	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	0.407***	6.679***	0.115***	0.260***
	(0.000)	(0.000)	(0.008)	(0.000)
Cash Flow/Assets	2.090***	20.443***	3.337***	4.378***
	(0.000)	(0.009)	(0.000)	(0.000)
Leverage	-0.335	-9.353*	-0.623	-0.107
	(0.370)	(0.075)	(0.256)	(0.860)
CAPX/Assets	15.503***	273.999***	16.987***	15.459***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D Exp./Assets	6.771***	101.517***	9.985***	8.306***
	(0.000)	(0.000)	(0.000)	(0.000)
PPE/Assets	-2.152***	-49.643***	-1.784*	-0.126
	(0.006)	(0.000)	(0.085)	(0.919)
Herfindahl Index	2.397*	10.260	-1.212	-6.479***
	(0.050)	(0.551)	(0.446)	(0.001)
Constant	-27.100***	-337.820***	-33.080***	-56.736***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	102302	102302	32708	33444
Adj. R^2	0.250	0.223	0.319	0.288
Year F. E.	Yes	Yes	Yes	Yes
Industry F. E.	Yes	Yes	Yes	Yes

Table II.5
Dual-Class Shares, Firm Financial Constraints, and Innovation

This table reports the estimation results of regressions designed to measure the effect of dual-class shares on innovation productivity for firms with different degrees of financial constraints. We use the KZ Index of Kaplan and Zingales (1997) to measure financial constraints and regress firm innovation output in year *t* on a Dual-Class dummy variable that equals one if a firm has dual-class shares in year *t* and zero otherwise, and the product of the Dual-Class dummy variable with Firm KZ Index for each firm in each year. The dependent variables are the measures of innovation productivity: Patent Number, Citation Number, Generality, and Originality. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets. Leverage, R&D Expense-to-Assets, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl Index based on the three-digit SIC code, as well as year and two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

	Patent Number (1)	Citation Number (2)	Generality (3)	Originality (4)
Dual-Class	-6.352***	-74.906***	-3.844***	-4.982***
	(0.000)	(0.000)	(0.000)	(0.000)
Dual-Class* KZ Index	1.318*	15.731	0.214	1.598*
	(0.062)	(0.112)	(0.787)	(0.075)
KZ Index	0.000	0.005	0.004	0.007
	(0.632)	(0.734)	(0.476)	(0.349)
Ln(Total Assets)	6.497***	83.199***	5.215***	5.798***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	0.151***	1.804***	0.003	0.055***
	(0.000)	(0.000)	(0.741)	(0.000)
ROA	-7.020***	-76.568***	-9.321***	-10.404***
	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	0.424***	7.149***	0.067	0.226***
	(0.000)	(0.000)	(0.140)	(0.000)
Cash Flow/Assets	2.021***	20.794**	3.909***	4.843***
	(0.000)	(0.010)	(0.000)	(0.000)
Leverage	-0.522	-14.575***	-0.649	-0.438
	(0.173)	(0.007)	(0.258)	(0.484)
CAPX/Assets	28.195***	470.014***	30.565***	30.047***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D Exp./Assets	8.753***	145.771***	11.595***	10.066***
	(0.000)	(0.000)	(0.000)	(0.000)
PPE/Assets	-7.467***	-126.117***	-8.008***	-7.201***
	(0.000)	(0.000)	(0.000)	(0.000)
Herfindahl Index	6.821***	35.812***	2.217**	1.004
	(0.000)	(0.001)	(0.020)	(0.382)
Constant	-27.850***	-342.692***	-31.780***	-48.411***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	102260	102260	32699	33438
Adj. R^2	0.193	0.169	0.230	0.214
Year F. E.	Yes	Yes	Yes	Yes
Industry F. E.	Yes	Yes	Yes	Yes

Table II.6

Dual-Class Shares, Firm Cash Flow, and Innovation

This table reports the estimation results of regressions designed to measure the effect of dual-class shares on innovation productivity for firms with different levels of cash flow. We regress firm innovation output in year *t* on a Dual-Class dummy variable that equals one if a firm has dual-class shares in year *t* and zero otherwise, and the product of the Dual-Class dummy variable with firm Cash Flow-to-Assets for each firm in each year. The dependent variables are the measures of innovation productivity: Patent Number, Citation Number, Generality and Originality. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, R&D Expense-to-Assets, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl Index based on the three-digit SIC code, as well as year and two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

	Patent Number	Citation Number	Generality	Originality
	(1)	(2)	(3)	(4)
Dual-Class	-3.838***	-52.407***	-3.575***	-2.338**
	(0.000)	(0.000)	(0.000)	(0.037)
Dual-Class*Cash Flow/Assets	-21.111**	-141.849	-1.273	-17.736
	(0.039)	(0.322)	(0.910)	(0.149)
Ln(Total Assets)	6.496***	83.180***	5.210***	5.797***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	0.151***	1.802***	0.004	0.054***
	(0.000)	(0.000)	(0.730)	(0.000)
ROA	-6.948***	-76.014***	-9.210***	-10.241***
	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	0.426***	7.157***	0.069	0.232***
	(0.000)	(0.000)	(0.128)	(0.000)
Cash Flow/Assets	2.004***	20.700**	3.847***	4.780***
	(0.001)	(0.011)	(0.000)	(0.000)
Leverage	-0.482	-14.022***	-0.622	-0.283
	(0.205)	(0.009)	(0.272)	(0.648)
CAPX/Assets	28.185***	469.655***	30.357***	30.031***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D Expense/Assets	8.805***	146.287***	11.681***	10.197***
	(0.000)	(0.000)	(0.000)	(0.000)
PPE/Assets	-7.447***	-125.870***	-7.899***	-7.147***
	(0.000)	(0.000)	(0.000)	(0.000)
Herfindahl Index	6.819***	35.543***	2.220**	1.005
	(0.000)	(0.001)	(0.019)	(0.382)
Constant	-27.881***	-342.835***	-31.796***	-48.465***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	102302	102302	32708	33444
Adj. R^2	0.193	0.169	0.230	0.214
Year F. E.	Yes	Yes	Yes	Yes
Industry F. E.	Yes	Yes	Yes	Yes

Table II.7
Dual-Class Shares, High-Tech Industries, and Innovation

This table reports the estimation results of regressions designed to measure how the effects of dual-class shares on innovation productivity vary between High-Tech industries and other industries. Following Hall and Lerner (2009), we define the high-technology industries as drugs, office and computing equipment, communications equipment and electronic components. We regress firm innovation output in year *t* on a Dual-Class dummy variable that equals one if a firm has dual-class shares in year *t* and zero otherwise, a High-Tech dummy variable that equals one if a firm is within the high-tech industries in year *t* and zero otherwise, and the product of these two dummy variables. The dependent variables are the measures of innovation productivity; Patent Number, Citation Number, Generality and Originality. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, R&D Expense-to-Assets, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl Index based on the three-digit SIC code, as well as year and two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

	Patent Number	Citation Number	Generality	Originality
	(1)	(2)	(3)	(4)
Dual-Class	-6.716***	-72.965***	-3.834***	-4.654***
	(0.000)	(0.000)	(0.000)	(0.000)
Dual-Class* High-Tech	5.128***	39.289**	0.435	2.887**
	(0.000)	(0.019)	(0.728)	(0.043)
High-Tech	3.070***	67.064***	1.552***	2.141***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Total Assets)	6.499***	83.309***	5.198***	5.780***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	0.159***	1.970***	0.008	0.061***
	(0.000)	(0.000)	(0.419)	(0.000)
ROA	-7.007***	-77.131***	-9.238***	-10.300***
	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	0.416***	6.985***	0.060	0.220***
	(0.000)	(0.000)	(0.183)	(0.000)
Cash Flow/Assets	1.862***	17.797**	3.699***	4.611***
	(0.001)	(0.028)	(0.000)	(0.000)
Leverage	-0.406	-12.402**	-0.599	-0.233
	(0.287)	(0.020)	(0.290)	(0.707)
CAPX/Assets	26.831***	441.047***	29.185***	28.330***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D Expense/Assets	7.533***	118.828***	10.816***	9.161***
	(0.000)	(0.000)	(0.000)	(0.000)
PPE/Assets	-6.811***	-112.156***	-7.306***	-6.271***
	(0.000)	(0.000)	(0.000)	(0.000)
Herfindahl Index	8.550***	72.318***	3.383***	2.869**
	(0.000)	(0.000)	(0.001)	(0.018)
Constant	-31.337***	-433.053***	-36.464***	-50.854***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	102302	102302	32708	33444
Adj. R^2	0.194	0.170	0.230	0.214
Year F. E.	Yes	Yes	Yes	Yes
Industry F. E.	Yes	Yes	Yes	Yes

Table II.8

Dual-Class Shares, Hard-to-Innovate Industries, and Innovation

This table reports the estimation results of regressions designed to measure how the effects of dual-class shares on innovation productivity vary between Hard-to-Innovate industries and other industries. As in Hall, Jaffe, and Trajtenberg (2005) and Tian and Wang (2014) we define the Hard-to-Innovate industries as the pharmaceutical, medical instrumentation, chemicals, computers, communications, and electrical industries. We regress firm innovation output in year *t* on a Dual-Class dummy variable that equals one if a firm has dual-class shares in year *t* and zero otherwise, a Hard-to-Innovate dummy variable that equals one if a firm is within the hard-to-innovate industries in year *t* and zero otherwise, and the product of these two dummy variables. The dependent variables are the measures of innovation productivity: Patent Number, Citation Number, Generality and Originality. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, R&D Expense-to-Assets, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl Index based on the three-digit SIC code, as well as year and two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

	Patent Number	Citation	Generality	Originality
	(1)	(2)	(3)	(4)
Dual-Class	-6.600***	-75.833***	-3.791***	-4.501***
	(0.000)	(0.000)	(0.000)	(0.000)
Dual-Class * Hard-to-Innovate	5.920***	60.477***	0.346	2.964*
	(0.000)	(0.001)	(0.796)	(0.051)
Hard-to-Innovate	3.180***	69.030***	1.987***	2.494***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln (Total Assets)	6.492***	83.131***	5.191***	5.770***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	0.159***	1.983***	0.010	0.062***
	(0.000)	(0.000)	(0.342)	(0.000)
ROA	-7.035***	-77.629***	-9.270***	-10.359***
	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	0.414***	6.968***	0.057	0.217***
	(0.000)	(0.000)	(0.207)	(0.000)
Cash Flow/Assets	1.869***	17.951**	3.653***	4.596***
	(0.001)	(0.026)	(0.000)	(0.000)
Leverage	-0.377	-11.949**	-0.594	-0.206
	(0.322)	(0.025)	(0.294)	(0.739)
CAPX/Assets	26.852***	441.145***	28.876***	28.134***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D Expense/Assets	7.500***	118.262***	10.544***	8.957***
	(0.000)	(0.000)	(0.000)	(0.000)
PPE/Assets	-6.781***	-111.552***	-7.133***	-6.143***
	(0.000)	(0.000)	(0.000)	(0.000)
Herfindahl Index	8.647***	74.526***	3.770***	3.203***
	(0.000)	(0.000)	(0.000)	(0.008)
Constant	-28.809***	-363.278***	-32.479***	-49.408***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	102302	102302	32708	33444
Adj. R^2	0.194	0.170	0.231	0.215
Year F. E.	Yes	Yes	Yes	Yes
Industry F. E.	Yes	Yes	Yes	Yes

Table II.9
Dual-Class Shares, Takeover Threats, and Innovation

This table reports the estimation results of regressions designed to measure the effect of dual-class shares on innovation productivity for firms with different exposures to external takeover threats. We use the state-level index (from 0 to 5) of anti-takeover laws compiled by Bebchuk and Cohen (2003) as a proxy for external takeover pressure and regress firm' innovation output in year *t* on a Dual-Class dummy variable that equals one if a firm has dual-class shares in year *t* and zero otherwise, and the product of the Dual-Class dummy variable with the firm Anti-Takeover Index for each firm in each year. The dependent variables are the measures of innovation productivity: Patent Number, Citation Number, Generality and Originality. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, R&D Expense-to-Assets, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl Index based on the three-digit SIC code, as well as year and two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

	Patent Number	Citation Number	Generality	Originality
	(1)	(2)	(3)	(4)
Dual-Class	-1.971	-34.506	-3.644**	-1.603
	(0.138)	(0.116)	(0.014)	(0.327)
Dual-Class* Anti-Takeover Index	-1.140***	-15.518**	0.046	-0.633
	(0.004)	(0.019)	(0.916)	(0.190)
Anti-Takeover Index	-0.208**	-8.151***	-0.250***	-0.245**
	(0.012)	(0.000)	(0.005)	(0.013)
Ln(Total Assets)	6.484***	107.264***	5.034***	5.630***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	0.363***	4.600***	0.138***	0.187***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-7.277***	-120.505***	-9.938***	-10.238***
	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	0.433***	8.404***	0.137***	0.255***
	(0.000)	(0.000)	(0.005)	(0.000)
Cash Flow/Assets	1.978**	33.362**	3.677***	3.939***
	(0.015)	(0.013)	(0.001)	(0.000)
Leverage	-0.233	-11.725	-1.366**	-1.204*
	(0.659)	(0.179)	(0.047)	(0.100)
CAPX/Assets	21.734***	445.535***	22.488***	20.655***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D Expense/Assets	7.674***	128.573***	7.923***	7.670***
	(0.000)	(0.000)	(0.000)	(0.000)
PPE/Assets	-3.249***	-78.387***	-3.335**	-3.119**
	(0.003)	(0.000)	(0.014)	(0.036)
Herfindahl Index	3.659	57.633	8.896***	3.534
	(0.162)	(0.181)	(0.005)	(0.316)
Constant	-29.554***	-447.845***	-34.210***	-29.541***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	47047	47047	17744	19385
Adj. R^2	0.224	0.209	0.239	0.235
Year F. E.	Yes	Yes	Yes	Yes
Industry F. E.	Yes	Yes	Yes	Yes

Table II.10

Dual-Class Shares, Product Market Competition, and Innovation

This table reports estimation results of regressions designed to measure the effect of dual-class shares on innovation productivity for firms facing different levels of product market competition. We use the Herfindahl Index of Herfindahl (1950) as a proxy for the level of product market competition and regress firm innovation output in year *t* on a Dual-Class dummy variable that equals one if a firm has dual-class shares in year *t* and zero otherwise, and the product of the Dual-Class dummy variable with the firm Herfindahl Index for each firm in each year. The dependent variables are the measures of innovation productivity: Patent Number, Citation Number, Generality and Originality. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, R&D Expense-to-Assets, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl Index based on the three-digit SIC code, as well as year and two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

	Patent Number	Citation Number	Generality	Originality
	(1)	(2)	(3)	(4)
Dual-Class	0.106	-6.732	-2.370*	-0.875
	(0.931)	(0.694)	(0.064)	(0.548)
Dual-Class*Herfindahl Index	-34.022***	-352.646***	-8.400	-19.611**
	(0.000)	(0.001)	(0.317)	(0.038)
Ln(Total Assets)	6.607***	85.616***	5.076***	5.684***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	0.195***	2.470***	0.042***	0.095***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-7.740***	-89.486***	-9.942***	-11.283***
	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	0.419***	6.925***	0.068	0.228***
	(0.000)	(0.000)	(0.127)	(0.000)
Cash Flow/Assets	2.152***	22.581***	3.996***	5.253***
	(0.000)	(0.005)	(0.000)	(0.000)
Leverage	-0.295	-9.733*	-0.579	-0.165
	(0.432)	(0.066)	(0.298)	(0.787)
CAPX/Assets	17.974***	314.330***	19.573***	17.588***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D Expense/Assets	6.908***	111.578***	9.585***	8.466***
	(0.000)	(0.000)	(0.000)	(0.000)
PPE/Assets	-2.539***	-53.159***	-2.524**	-1.016
	(0.001)	(0.000)	(0.014)	(0.406)
Herfindahl Index	4.113***	31.325*	2.536	-0.964
	(0.001)	(0.071)	(0.120)	(0.642)
Constant	-28.271***	-355.947***	-33.862***	-47.927***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	102302	102302	32708	33444
Adj. R^2	0.228	0.201	0.279	0.254
Year F. E.	Yes	Yes	Yes	Yes
Industry F. E.	Yes	Yes	Yes	Yes

Table II.11

Firms Switching from Single-Class to Dual-Class Share Structures

This table reports the estimation results of panel regressions examining the effects of dual-class shares on innovation productivity the period from 1970 through 2006. Only firms that changed from single-class to dual-class share structures are included in the sample. The dependent variables in Columns (1) to (4) are the Patent Number (the number of patent applications filed in a given year that are eventually granted), Citation Number(the number of citations received for patent applications filed in a given year that are eventually granted), Generality (the sum of generality scores of all successful patent applications filed by a firm in each year), and Originality (the sum of originality scores of all successful patent applications filed by a firm in each year). The main independent variable is Dual-Class, which equals one if a firm has dual-class shares in year t and zero otherwise. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, R&D Expense-to-Assets, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl Index based on the three-digit SIC code, as well as year and two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

	Patent Number	Citation Number	Generality	Originality
	(1)	(2)	(3)	(4)
Dual-Class	-4.764***	-65.544***	-3.081***	-2.785***
	(0.000)	(0.000)	(0.000)	(0.006)
Ln(Total Assets)	7.161***	89.882***	3.516***	5.128***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	0.044	1.128**	0.024	-0.029
	(0.211)	(0.028)	(0.404)	(0.471)
ROA	-5.203	-64.215	-5.018	-1.042
	(0.140)	(0.210)	(0.161)	(0.802)
Tobin's Q	1.169***	21.147***	0.488***	0.657***
	(0.000)	(0.000)	(0.001)	(0.001)
Cash Flow/Assets	2.864	70.886	4.231	0.323
	(0.339)	(0.103)	(0.167)	(0.911)
Leverage	-2.388	-8.992	0.341	-0.997
	(0.156)	(0.713)	(0.832)	(0.648)
CAPX/Assets	42.612***	772.518***	37.143***	32.700***
	(0.000)	(0.000)	(0.000)	(0.005)
R&D Expense/Assets	31.353***	433.537***	12.513***	26.681***
	(0.000)	(0.000)	(0.005)	(0.000)
PPE/Assets	0.744	-28.887	0.211	8.240*
	(0.817)	(0.536)	(0.944)	(0.053)
Herfindahl Index	-1.720	-55.635	-8.170***	-16.401***
	(0.575)	(0.212)	(0.008)	(0.000)
Constant	-34.280***	-499.380***	-27.566***	-29.408
	(0.000)	(0.000)	(0.000)	(0.212)
Observations	6893	6893	2310	2452
Adj. R^2	0.197	0.176	0.204	0.190
Year F. E.	Yes	Yes	Yes	Yes
Industry F. E.	Yes	Yes	Yes	Yes

Table II.12

Research and Development Expense and Share Class Structure

This table reports the estimation results of panel regressions examining the effects of dual-class shares on firm Research and Development Expenditures. The results reported in Column (1) are based on our full sample from 1970 through 2006. Column (2) includes only firms that switched from single to dual-class share structures. The dependent variable in Columns (1) and (2) is the R&D Expense-to-Assets for each firm in each year. The main independent variable in Columns (1) and (2) is Dual-Class, which equals one if the firm has dual-class shares and zero for firms with single-class shares. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl Index based on the three-digit SIC code, as well as year and two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

	R&D Expense-to-Assets	
	(1)	(2)
Dual-Class	-0.011***	-0.002
	(0.000)	(0.244)
Ln(Total Assets)	-0.001***	-0.003***
	(0.000)	(0.000)
Firm Age	-0.001***	-0.001***
	(0.000)	(0.000)
ROA	-0.202***	-0.185***
	(0.000)	(0.000)
Tobin's Q	-0.000*	0.003***
	(0.052)	(0.000)
Cash Flow/Assets	-0.024***	-0.035***
	(0.000)	(0.000)
Leverage	-0.046***	-0.053***
	(0.000)	(0.000)
CAPX/Assets	0.226***	0.197***
	(0.000)	(0.000)
PPE/Assets	-0.045***	-0.039***
	(0.000)	(0.000)
Herfindahl Index	-0.054***	-0.004
	(0.000)	(0.563)
Constant	0.096***	0.126***
	(0.000)	(0.000)
Observations	102302	6893
Adj. R^2	0.520	0.555
Year F. E.	Yes	Yes
Industry F. E.	Yes	Yes

Table II.13

Innovation Efficiency and Share Class Structure

This table reports the estimation results of panel regressions examining the effects of dual-class shares on firm Innovation Efficiency (Hirshleifer, Hsu and Li, 2013), which is defined as number of patent applications filed in a given year that are eventually granted divided by the R&D Expense of previous years. The results reported in Column (1) are based on our full sample from 1970 through 2006. Column (2) includes only firms that switched from single to dual-class share structures. The dependent variable in Columns (1) and (2) is the Innovation Efficiency measure for each firm in each year. The main independent variable in Columns (1) and (2) is Dual-Class, which equals one if the firm has dual-class shares and zero for firms with single-class shares. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, R&D Expense-to-Assets, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl Index based on the three-digit SIC code, as well as year, two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

	Innovation Efficiency	
	(1)	(2)
Dual-Class	-0.097*	-0.064**
	(0.069)	(0.038)
Ln(Total Assets)	-0.074***	-0.051*
	(0.000)	(0.063)
Firm Age	-0.008***	-0.009***
	(0.000)	(0.003)
ROA	-0.099**	0.049
	(0.046)	(0.843)
Tobin's Q	0.013**	0.012
	(0.016)	(0.590)
Cash Flow/Assets	0.070**	-0.158
	(0.046)	(0.286)
Leverage	-0.144***	-0.342***
	(0.010)	(0.004)
CAPX/Assets	1.343***	2.385*
	(0.001)	(0.055)
R&D Expense/Assets	-0.789***	-0.795**
	(0.001)	(0.041)
PPE/Assets	0.023	0.628
	(0.825)	(0.104)
Herfindahl Index	0.027	-0.088
	(0.859)	(0.781)
Constant	0.160	-0.222
	(0.299)	(0.453)
Observations	60096	3900
Adj. R^2	0.062	0.064
Year F. E.	Yes	Yes
Industry F. E.	Yes	Yes

Table II.14

Innovation Efficiency– Subsample Tests

This table reports the estimation results of panel regressions examining the effects of dual-class shares on firm Innovation Efficiency (Hirshleiferet al., 2013), which is defined as the number of patent applications filed in a given year that are eventually granted divided by the R&D Expense of previous years. The results are based on our full sample from 1970 through 2006. The dependent variable in each regression is the innovation efficiency for each firm in each year. The dichotomous subsamples are as follows: old vs. young firms, columns (1) and (2);hard- vs. easy-to-innovate industries, columns (3) and (4);high- vs. low-tech industries, columns (5) and (6); and high vs. low takeover threats, columns (7) and (8). Subsample sorting is based on the full sample medians of the conditioning variables. The main independent variable is Dual-Class, which equals one if the firm has dual-class shares and zero for firms with Single-class shares. All regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, R&D Expense-to-Assets, CAPX-to-Assets, PPE-to-Assets, and the Herfindahl index based on the three-digit SIC code, as well as year and two-digit SIC industry fixed effects. Detailed definitions of each variable are provided in the Appendix. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively using *t*-statistics for two-tailed tests. The p-values are reported in parentheses.

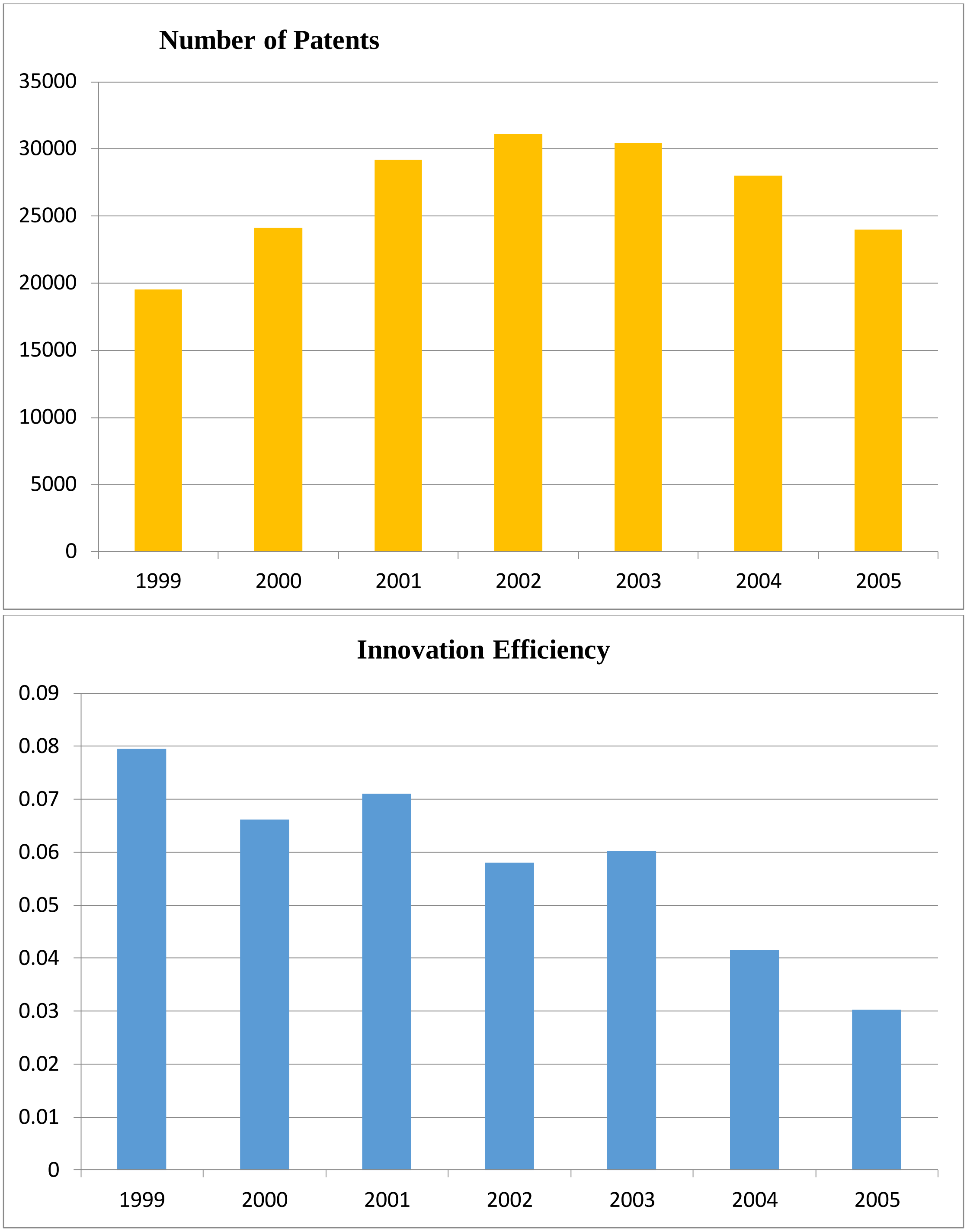
	Age		Innovation Difficulty		High-Tech Industries		Takeover Threat	
	Old	Young	Hard	Easy	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dual-Class	-0.108***	-0.003	0.008	-0.141**	0.018	-0.168**	-0.030	-0.124**
	(0.004)	(0.977)	(0.897)	(0.036)	(0.664)	(0.021)	(0.688)	(0.047)
Ln (Total Assets)	-0.061***	-0.092***	-0.047***	-0.087***	-0.056***	-0.090***	-0.015**	-0.087***
	(0.001)	(0.000)	(0.004)	(0.000)	(0.005)	(0.000)	(0.031)	(0.000)
Firm Age	-0.004***	-0.041***	-0.010***	-0.008***	-0.012***	-0.007***	-0.012***	-0.008***
	(0.001)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-0.040	-0.077	-0.065	-0.107	-0.070	-0.098	-0.244***	-0.070
	(0.573)	(0.385)	(0.253)	(0.177)	(0.104)	(0.294)	(0.000)	(0.230)
Tobin's Q	0.011*	0.017**	0.019**	0.011**	0.016***	0.013**	0.027***	0.007
	(0.054)	(0.029)	(0.031)	(0.021)	(0.010)	(0.031)	(0.002)	(0.178)
Cash Flow/Assets	0.027	0.087	0.037***	0.086	0.035***	0.097	0.093**	0.057
	(0.599)	(0.112)	(0.000)	(0.120)	(0.000)	(0.149)	(0.026)	(0.154)
Leverage	-0.174**	-0.105	-0.100	-0.172**	-0.155***	-0.144	-0.270***	-0.099
	(0.033)	(0.334)	-0.265	(0.032)	(0.000)	(0.162)	(0.000)	(0.112)
R&D Expense/Assets	1.292***	0.930	1.246**	1.533***	1.659***	1.247***	1.519***	1.321***
	(0.000)	(0.210)	(0.046)	(0.000)	(0.003)	(0.007)	(0.000)	(0.004)
CAPX/Assets	-0.710***	-0.776***	-0.619**	-0.894***	-0.621**	-1.025***	-0.835***	-0.804***
	(0.008)	(0.001)	(0.049)	(0.000)	(0.020)	(0.000)	(0.000)	(0.008)
PPE/Assets	0.059	0.061	0.159	-0.080	0.022	-0.044	-0.122	0.067
	(0.430)	(0.755)	(0.206)	(0.563)	(0.865)	(0.787)	(0.232)	(0.562)
Herfindahl Index	0.263	-0.437	0.391	-0.083	-0.178	-0.079	-0.031	0.045
	(0.174)	(0.121)	(0.427)	(0.603)	(0.487)	(0.651)	(0.842)	(0.798)
Constant	0.146***	0.401	-0.022	0.267	0.277*	0.421	0.573***	0.494
	(0.005)	(0.026)	(0.905)	(0.253)	(0.067)	(0.977)	(0.000)	(0.333)
Observations	37484	22612	16788	43308	26219	33877	12519	47577
Adj. R^2	0.063	0.070	0.058	0.062	0.065	0.061	0.050	0.063
Year F. E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix C Tables for Part III

Variable Definitions

Variable	Definition
Innovation measures	
Patent Number	Patent number is defined as number of patent applications filed in year *t* of each firm. Only patents that are later granted are included. The patent number is set to zero for companies that have no patent information available from the NBER database.
Innovation efficiency	number of patent scaled by the previous four years' R&D investment (Hershleifer, Hsu and Li, 2013).
Control variables	
Ln(Asset)	The logarithm of the book value of total assets (AT from COMPUSTAT) measured at the end of fiscal year *t*.
Age	The logarithm of the book value of total assets (AT from COMPUSTAT) measured at the end of fiscal year *t*.
ROA	Firm operating income before depreciation (OIBDP from COMPUSTAT) divided by the book value of total assets (AT), measured at the end of fiscal year *t*.
Tobin's Q	The market value of equity (PRCC_F ×CSHO from COMPUSTAT) plus the book value of assets (AT) minus the book value of equity (CEQ from COMPUSTAT) minus balance sheet deferred taxes (TXDB from COMPUSTAT)] divided by the book value of assets (AT), measured at the end of fiscal year *t*.
Cash Flow-to-Assets	Income before extraordinary items (IB from COMPUSTAT) plus depreciation and amortization (DP from COMPUSTAT) divided by the book value of assets (AT), measured at the end of fiscal year *t*.
Leverage	The book value of debt (DLTT+DLC from COMPUSTAT) divided by the book value of total assets (AT) measured at the end of fiscal year *t*.
R&D Expense-to-Assets	Research and develop expenditure (XRD from COMPUSTAT) divided by the book value of assets (AT), measured at the end of fiscal year *t*.
CAPX-to-Assets	Capital expenditure (CAPX from COMPUSTAT) divided by book value of assets (AT), measured at the end of fiscal year *t*.
Herfindahl Index	Herfindahl index of 3-digit SIC industry of each firm measured at the end of fiscal year *t* based on sales.

Figure III.1: Innovation Productivity over Time, 1999 – 2005



Notes: This figure plots trends in total *Patent Number* and sample mean of innovation efficiency (Hirshleifer, Hsu and Li, 2013) over the sample period 1999 – 2005.

Table III.1: Summary and Univariate Test

	3 years pre- SOX				3 years post- SOX				Comparison between two samples
	Obs	Mean	Median	S.D.	Obs	Mean	Median	S.D.	Mean-Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Innovation Productivity Measurement									
Log(1+Patent)	20153	0.41	0.00	1.00	20143	0.40	0.00	1.01	-0.01
									(1.29)
Innovation Effeciency	20153	0.07	0.00	1.13	20143	0.04	0.00	0.63	-0.03***
									(3.11)
Panel B: Control Variables									
Log (Total Asset)	18594	5.37	5.54	2.71	18745	5.60	5.84	2.82	0.23
Firm Age	20153	14.18	9.00	12.90	20143	18.17	13.00	12.88	3.98
ROA	18594	-0.11	0.07	0.88	18745	-0.14	0.07	1.22	-0.04
Tobin's Q	18594	3.21	1.24	7.76	18745	3.74	1.46	12.00	0.52
Cash	18594	-0.19	0.04	1.14	18745	-0.23	0.05	1.63	-0.04
Leverage Ratio	18594	0.29	0.20	0.42	18745	0.33	0.18	0.72	0.04
CAPX	18594	0.05	0.03	0.07	18745	0.04	0.02	0.05	-0.01
R&D Expense	18594	0.06	0.00	0.15	18745	0.05	0.00	0.14	0.00
Herfindahl Index	20153	0.18	0.10	0.23	20143	0.19	0.11	0.24	0.02

Notes:
This table reports descriptive statistics for the sample of firms with innovation data in both pre-SOX (1999-2001) and post-SOX (2003-2005) periods. Columns (1) to (4) and (5) to (8) report the number of observations (N), mean median and standard deviation (S.D.) of the subsample that cover three years before and after the Sarbanes-Oxley Act (SOX), respectively. Column (9) report the difference of mean of each variable for the two subsamples. In Panel A, two innovation measures are listed: the logarithm of one plus the number of successfully granted patent applications filed in each year of each firm, and the firms' *Innovative Efficiency* (Hirshleifer, Hsu and Li, 2013), which is defined by using number of patent application that is eventually granted divided by the R&D Expense of previous years. And Panel B includes all of the control variables: logarithm of total asset, firm age, return on asset (ROA), Tobin's Q, leverage, R&D expense, capital expenditure (CAPX) and Herfindahl Index based on the three-digit SIC code. Column (9) reports the difference in means between the two groups. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively using t-statistics for two-tailed tests.

Table III. 2: Correlation Matrix

	Patent	Innov. Eff.	Log(Asset)	Firm Age	ROA	Tobin's Q	Cash Flow /Assets	Leverage	CAPEX/ Assets	R&D Expense/ Assets	Hindex	G Index	KZ Index
Patent	1.000												
Innovation Efficiency	0.063	1.000											
Log(Asset in $ millions)	0.151	0.004	1.000										
Firm Age (years)	0.149	0.020	0.376	1.000									
ROA	0.048	0.008	0.097	0.056	1.000								
Tobin's Q	0.218	0.002	-0.192	-0.176	-0.008	1.000							
Cash Flow/Assets	0.024	0.007	0.119	0.066	0.894	-0.043	1.000						
Leverage	-0.066	0.002	0.156	0.116	-0.279	-0.121	-0.265	1.000					
CAPEX/Assets	-0.030	0.005	-0.103	-0.007	0.209	0.100	0.170	0.006	1.000				
R&D Expense/Assets	0.372	0.005	-0.291	-0.200	-0.321	0.327	-0.306	-0.016	-0.066	1.000			
Hindex	-0.006	-0.004	-0.019	0.110	0.098	-0.044	0.069	-0.009	0.060	-0.171	1.000		
G Index	0.054	-0.003	0.147	0.320	0.044	-0.090	0.038	0.045	-0.018	-0.083	0.045	1.000	
KZ Index	-0.030	-0.001	0.108	-0.035	-0.076	0.060	-0.115	0.370	-0.002	-0.032	-0.023	0.010	1.000

Table III.3: Baseline Regression of Impact of SOX on innovation

	Log(1+Patent)		Innovation Efficiency	
	(1)	(2)	(3)	(4)
SOX Signal	0.041***	-0.115***	-0.038***	-0.055***
	(3.57)	(-6.64)	(-4.62)	(-3.87)
Log Total Asset		0.171***		-0.002
		(5.14)		(-0.90)
Firm Age		0.007***		0.001
		(3.17)		(0.86)
ROA		0.011		-0.005
		(0.65)		(-1.25)
Tobin's Q		0.012***		0.000*
		(4.22)		(1.84)
Cash		-0.019***		0.005
		(-2.81)		(1.41)
Leverage		-0.096***		-0.017***
		(-3.06)		(-3.20)
CAPEX		0.248		0.029
		(0.73)		(0.53)
R&D Expense		0.537***		-0.112***
		(4.34)		(-2.75)
Hindex		0.161		-0.025
		(0.80)		(-0.68)
Constant	0.357***	-0.807***	0.029***	0.043*
	(15.88)	(-3.93)	(3.50)	(1.91)
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	40296	37339	40296	37339
adj. R-sq	0.188	0.344	0.004	0.004

Notes: This table reports the OLS estimation results of the baseline panel regressions examining the effects of Sarbanes-Oxley Act on innovation productivity from year 1999 to 2005 (without 2002). The dependent variables in Columns (1) to (2) are the logarithm of one plus the number of successfully granted patent applications filed in each year of each firm and the dependent variables in Columns (3) to (4) is firms' *Innovative Efficiency* (Hirshleifer, Hsu and Li, 2013). The main independent variable is SOX Signal, which equals to one if observations are of years no less than 2002 and zero otherwise. All regressions control for the logarithm of total asset, firm age, return on asset (ROA), Tobin's Q, leverage, R&D expense, capital expenditure (CAPX), Herfindahl Index based on the three-digit SIC code, as well as year, two-digit SIC industry. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the industry (two-digit SIC code) and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table III.4: Impact of SOX on high Q vs. low Q firms

	Log(1+Patent)		Innovation Efficiency	
	High Q	Low Q	High Q	Low Q
	(1)	(2)	(3)	(4)
SOX Signal	-0.202***	-0.015	-0.064***	-0.047
	(-5.59)	(-0.72)	(-4.24)	(-1.04)
Log Total Asset	0.212***	0.117***	-0.003	-0.002
	(5.83)	(4.34)	(-0.78)	(-0.54)
Firm Age	0.011***	0.003*	0.000	0.001
	(4.40)	(1.93)	(0.21)	(0.86)
ROA	-0.030**	-0.031	-0.008	-0.006
	(-2.03)	(-0.43)	(-1.03)	(-0.27)
Tobin's Q	0.010***	0.330***	-0.000	0.053*
	(4.33)	(4.29)	(-0.75)	(1.95)
Cash	-0.010*	-0.007	0.005	0.005
	(-1.79)	(-0.16)	(1.51)	(0.36)
Leverage	-0.051**	-0.361***	-0.017**	-0.002
	(-2.07)	(-5.85)	(-2.42)	(-0.06)
CAPEX	0.203	0.096	0.017	0.004
	(0.54)	(0.40)	(0.32)	(0.04)
R&D Expense	0.427***	0.930**	-0.126***	-0.184*
	(4.24)	(2.05)	(-3.06)	(-1.94)
Hindex	-0.099	0.362**	0.038	-0.076
	(-0.41)	(1.98)	(0.67)	(-1.46)
Constant	-0.880***	-0.725***	0.056	-0.002
	(-3.62)	(-3.54)	(1.39)	(-0.07)
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	19501	17838	19501	17838
adj. R-sq	0.389	0.277	0.005	-0.000

Notes: This table reports the estimation results of subsample regressions examining how the effects of Sarbanes-Oxley (SOX) Act on innovation productivity vary between the high-growth firms and low-growth firm. In each year, firms with Tobin's Q that higher than median are considered as high-growth firms and low-growth otherwise. The dependent variables in Columns (1) to (2) are the logarithm of one plus the number of successfully granted patent applications filed in each year of each firm, and the dependent variables in Columns (3) to (4) is firms' *Innovative Efficiency* (Hirshleifer, Hsu and Li, 2013); the main independent variable is SOX Signal, which equals to one if observations are of years no less than 2002 and zero otherwise. All regressions control for the logarithm of total asset, firm age, return on asset (ROA), Tobin's Q, leverage, R&D expense, capital expenditure (CAPX), Herfindahl Index based on the three-digit SIC code, as well as year, two-digit SIC industry. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the industry (two-digit SIC code) and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table III.5: Impact of SOX on good governance vs. poor governance firms				
	Log(1+Patent)		Innovation Efficiency	
	Good G	Poor G	Good G	Poor G
	(1)	(2)	(3)	(4)
SOX Signal	-0.069	-0.155**	-0.030**	-0.332**
	(-1.14)	(-2.24)	(-2.09)	(-2.18)
Log Total Asset	0.415***	0.379***	0.007	-0.002
	(6.27)	(6.36)	(1.51)	(-0.17)
Firm Age	0.010***	0.004	-0.000	0.003
	(3.43)	(0.93)	(-0.20)	(0.96)
ROA	0.527	0.614***	0.061	0.064
	(1.11)	(3.13)	(0.96)	(0.70)
Tobin's Q	0.085***	0.097***	0.005	-0.002
	(4.00)	(4.69)	(1.64)	(-0.26)
Cash	-0.053	-0.398***	-0.024	-0.033
	(-0.13)	(-3.00)	(-0.64)	(-0.57)
Leverage	-0.518**	-0.407**	-0.040	-0.063
	(-2.25)	(-2.37)	(-1.22)	(-1.26)
CAPEX	0.590	-0.308	0.007	-0.279
	(0.40)	(-0.30)	(0.03)	(-0.58)
R&D Expense	7.032***	5.098**	-0.367	0.228*
	(5.31)	(2.54)	(-1.30)	(1.68)
Hindex	0.524	-0.200	0.019	-0.067
	(1.53)	(-0.48)	(0.28)	(-0.53)
Constant	0.476	-2.690***	0.088	0.215
	(0.80)	(-8.42)	(1.59)	(1.41)
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	3903	2980	3903	2980
adj. R-sq	0.587	0.539	0.042	-0.012

Notes: This table reports the estimation results of subsample regressions examining how the effects of Sarbanes-Oxley (SOX) Act on innovation productivity vary with the firms' level of corporate governance, which measured by G-Index. In each year, firms with G-Index that higher than median are considered as Good governance firms and Poor governance otherwise. The dependent variables in Columns (1) to (2) are the logarithm of one plus the number of successfully granted patent applications filed in each year of each firm, and the dependent variables in Columns (3) to (4) is firms' *Innovative Efficiency* (Hirshleifer, Hsu and Li, 2013); the main independent variable is SOX Signal, which equals to one if observations are of years no less than 2002 and zero otherwise. All regressions control for the logarithm of total asset, firm age, return on asset (ROA), Tobin's Q, leverage, R&D expense, capital expenditure (CAPX), Herfindahl Index based on the three-digit SIC code, as well as year, two-digit SIC industry. Robust t-statistics with standard errors clustered at the industry (two-digit SIC code) and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table III.6: Impact of SOX on high-tech vs. low-tech firms

	Log(1+Patent)		Innovation Efficiency	
	High Tech	Non-High	High Tech	Non-High
	(1)	(2)	(3)	(4)
SOX Signal	-0.151***	-0.035***	-0.055***	-0.023
	(-4.74)	(-3.60)	(-3.18)	(-0.75)
Log Total Asset	0.361***	0.113***	-0.003	-0.002
	(25.90)	(18.23)	(-0.42)	(-0.64)
Firm Age	0.010***	0.008***	-0.001	0.001
	(3.81)	(6.93)	(-0.65)	(1.21)
ROA	-0.091**	0.015	-0.007	-0.005
	(-2.37)	(1.18)	(-0.85)	(-0.53)
Tobin's Q	0.015***	0.008***	-0.000	0.000
	(6.82)	(10.17)	(-0.38)	(0.74)
Cash	-0.004	-0.013*	0.012	0.004
	(-0.19)	(-1.70)	(1.18)	(1.14)
Leverage	-0.089***	-0.078***	-0.003	-0.020**
	(-3.02)	(-5.90)	(-0.24)	(-2.38)
CAPEX	0.720**	-0.175	0.237***	-0.068
	(2.44)	(-1.52)	(3.21)	(-1.42)
R&D Expense	0.720***	0.642***	-0.169**	-0.045
	(8.44)	(7.51)	(-2.15)	(-1.32)
Hindex	-0.375	0.267**	-0.401**	0.019
	(-0.87)	(2.56)	(-2.36)	(0.46)
Constant	-2.351***	-0.461	0.080	0.035
	(-19.38)	(-1.41)	(1.09)	(1.41)
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	8790	28549	8790	28549
adj. R-sq	0.444	0.280	0.005	0.002

Notes: This table reports the estimation results of subsample regressions examining how the effects of Sarbanes-Oxley (SOX) Act on innovation productivity vary within high-technology industries and non-high-technology industries. As in Hall and Lerner (2010) the high-technology sectors include drugs, office and computing equipment, communications equipment and electronic components, and the rest are classified as non-high-technology sectors. The dependent variables in Columns (1) to (2) are the logarithm of one plus the patent number and the dependent variables in Columns (3) to (4) is firms' *Innovative Efficiency* (Hirshleifer, Hsu and Li, 2013); the main independent variable is SOX Signal, which equals to one if observations are of years no less than 2002 and zero otherwise. All regressions control for the logarithm of total asset, firm age, return on asset (ROA), Tobin's Q, leverage, R&D expense, capital expenditure (CAPX), Herfindahl Index based on the three-digit SIC code, as well as year, two-digit SIC industry. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the industry (two-digit SIC code) and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table III.7: Impact of SOX on firms gone private vs. remaining listed

	Log(1+Patent)	Log(1+Patent)
	(1)	(2)
SOX * Delisted Signal	0.188***	0.150***
	(5.72)	(4.42)
Delisted Signal	-0.531***	-0.210***
	(-11.25)	(-5.16)
SOX Signal	-0.245***	-0.357***
	(-13.68)	(-16.17)
Log (Total Asset)		0.254***
		(22.39)
Firm Age		0.003**
		(2.05)
ROA		-0.002
		(-1.64)
Tobin's Q		0.001***
		(4.49)
Cash Flow/Assets		0.001
		(1.26)
Leverage		0.001*
		(1.86)
CAPX/Assets		1.152***
		(5.11)
R&D Expense/Assets		0.009
		(0.99)
Herfindahl Index		0.291**
		(2.15)
Constant	1.501**	-0.422
	(2.00)	(-0.64)
Year F. E.	Yes	Yes
Industry F. E.	Yes	Yes
Observations	22013	21782
Adj. R^2	0.173	0.374

Notes: This table reports the estimation results of subsample regressions examining how the effects of Sarbanes-Oxley (SOX) Act on innovation productivity vary between firms did not delist until 2006 and firms delisted during 2001 to 2003. It use the NBER dataset to include sample of patent number for both listed and delisted firms. The sample period is from 1998 to 2006. The Delisted Signal equals to one if the firm delisted during 2001 to 2003 and zero otherwise. The dependent variables are measures of innovation productivity including patents; the main explanatory variable is the SOX Signal's interaction term with Delisted Signal. Regressions control for the logarithm of total assets, firm age, return on assets (ROA), Tobin's Q, Cash Flow-to-Assets, Leverage, R&D Expense-to-Assets, CAPX-to-Assets and Herfindahl Index based on the three-digit SIC code as well as year, two-digit SIC industry. Detailed definitions of each variable are provided in the Appendix. Robust t-statistics with standard errors clustered at the industry (two-digit SIC code) and year level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.