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On the Governance of Innovation: Institutional Ownership vs. Stock Price

Huong Thi Thu Le
Louisiana State University and Agricultural and Mechanical College

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INSTITUTIONAL OWNERSHIP VS. STOCK PRICE

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Huong Thi Thu Le
B.S., Foreign Trade University, 2001
M.A., Foreign Trade University, 2005
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ABSTRACT

Firms can change their outstanding shares to manage their stock price levels. Those with lower stock prices tend to attract more speculative trading, which causes higher price volatility and may force their managers to excessively focus on short-term earnings at the expense of R&D and other long-term projects. Thus, I hypothesize that keeping high stock price levels allows firms to (i) limit speculative traders' influences on stock prices and thus mitigate investor short-termism, and (ii) enhance R&D productivity. Indeed, I find that high-priced firms are less likely to cut R&D to reverse an earnings decline, less likely to fire their CEOs, and have more innovation. All these findings are robust after controlling for institutional ownership, a factor that has been shown in the literature to have a correlation with share price and also have a significant impact on R&D policies and innovation. For robustness checks, I examine stock splits, which allow mangers to re-set their stock price levels, and IPOs in which managers set an offering price range before shares are publicly traded. Consistent with my hypothesis, I discover that innovative firms are less likely to split their stocks, and that innovation declines after firms split their stocks. Furthermore, IPO firms that set higher offering prices, not those that attract more institutional ownership, have more future innovation. Thus, the results imply that, rather than being "forced" or "assured" by institutional investors to innovate as the extant literature suggests, managers of innovative firms actively support high stock price levels to foster innovation.

CHAPTER 1: INTRODUCTION

It is a common impression that institutional investors play a positive role in the governance of innovation in public traded companies. One reason, as Hall and Lerner (2009) suggest, is that institutional investors can better deal with the asymmetric information problems related to R&D. Also, Bushee (1998) shows that firms with more institutional ownership are less inclined to cut R&D following poor short-term earnings performance, suggesting that institutional investors tend to have long-term views on the firms they invest in. Aghion, Van Reenen, and Zingales (2013) further contrast two hypotheses—<u>the lazy manager hypothesis</u> in which managers prefer a quiet life and institutional investors' monitoring forces them to innovate, and <u>the career concern hypothesis</u> in which managers dislike the risk in pursuing innovation and institutional investors provide incentives for managers to innovate by reassuring their job security if bad outcomes occur. Their evidence favors the latter hypothesis.

However, one drawback of this line of inquiry is that managers are assumed to play a passive role. Specifically, managers seem need to be "forced" or "assured" by institutional investors to innovate as if they are not in control of corporate strategies. Another drawback is the assumption that institutional investors seemingly like the risk of innovation. Given that institutions' primary goal is to make money for their stakeholders, the risk of innovation could compromise that goal. Hence, institutional investors should dislike the risk of innovation as well, even though the extent of their dislike could be reduced (but would not disappear) by their informational advantage over retail investors which allows institutional investors to select firms that are better able to innovate, and by the size of their portfolios,

which allows them to diversify away some risk of innovation in firms they select to invest. Therefore, there is a need to rethink the role of managers in innovation and the role of institutional ownership in the governance of innovation.

This rethinking leads to a subtle factor ignored in the previous studies, namely stock price level, which is highly correlated to institutional ownership. As Dyl and Elliott (2006) point out, firms with more investor recognition (e.g., large firms and those that can attract more institutional investors) tend to keep higher stock price levels. They also note that managers take actions to set price levels for their stocks (i.e., by manipulating the number of shares outstanding, such as stock splits, stock dividends, and share buybacks). According to Brandt, Brav, Graham, and Kumar (2010), firms that set lower stock price levels tend to attract more speculative trading by retail investors and result in higher price volatility. Taken together, these findings imply a simple price-setting framework in which (i) managers are risk averse and dislike the high price volatility induced by speculative trading, and (ii) they prefer to set a high stock price level to preclude speculative traders from their investor base. The idea echoes Warren Buffett's explanation in his 1983 Chairman's letter to shareholders for why Berkshire Hathaway did not split its stock: "We try to attract investors who will understand our operations, attitudes and expectations. (And, fully as important, we try to dissuade those who won't.) […] Investors possessing those characteristics are in a small minority …"[1]

[1] Warren Buffett also noted in his 1983 Chairman's letter that "If the holders of a company's stock and/or the prospective buyers attracted to it are prone to make irrational or emotion-based decisions, some pretty silly stock prices are going to appear periodically. Manic-depressive personalities produce manic-depressive valuations. Such aberrations may help us in buying and selling the stocks of other companies. But we think it is in both your interest and ours to minimize their occurrence in the market for Berkshire… In large part, however, we feel that high quality ownership can be attracted and maintained if we consistently communicate our business and ownership philosophy - along with no other conflicting messages - and then let self selection follow its course." See http://www.berkshirehathaway.com/letters/1983.html

Thus, under the framework, a firm would keep its stock price at a high level when a sufficient number of long-term investors find the firm attractive and willing to invest their money with the intention of staying for a long time. Conversely, if the firm cannot attract enough long-term investors, it needs to keep its stock price at a relatively low level in order to attract short-term investors, who prefer to take smaller (risky) positions and tend to have more speculative trading than long-term investors. Consequently, a firm's stock price level could be informative about the characteristics of its investor base.

The price-setting framework leads to the following questions: Could managers set a high stock price level to mitigate investor short-termism? If yes, high stock price could function like institutional ownership in the governance of innovation, as previous studies have suggested. By setting a high stock price level, do the firm increase R&D productivity and innovate more? If yes, setting a high stock price level could play a prominent role in enhancing innovation. Given that firms that attract more institutional investors tend to set a higher price level, to what extent is the effect of institutional ownership on innovation, as documented in the literature, derived from its correlation with stock price level? Can stock price level subsume the effect of institutional ownership on innovation? The last two questions directly compare institutional ownership and stock price levels in horse races to see which one is a better measure to guard against short-termism and foster innovation.

The prices of high-priced stocks behave very differently from those of low-priced stocks. Brandt et al. (2010) demonstrate that the positive trend of idiosyncratic volatility in the 1990s and early 2000s in U.S. markets (Campbell, Lettau, Malkiel, and Xu, 2001) and the reversal of the volatility trend in more recent years are largely driven by short-term speculative trading by retail investors on low-priced stocks. Their findings illustrate that

short-term speculative trading on low-priced stocks is forceful and has a profound effect on their price volatility. Short-term speculative trading is detrimental to firm innovation because it can force managers to excessively focus on short-term earnings at the expense of long-term interests. In contrast, higher-priced stocks have lower price volatility, reflecting that they tend to attract more long-term investors. Thus, I hypothesize that keeping high stock price levels allows firms to (i) limit speculative traders to influencing stock prices and thus to mitigate investor short-termism, and (ii) enhance the productivity of R&D investments.

Consistent with this hypothesis I find that it is high-priced firms, not those with high institutional ownership as Bushee (1998) claims, which are less likely to cut R&D to reverse an earnings decline. Similarly, unlike Aghion et al.'s (2013) argument that firms with higher institutional ownership are more likely to keep their CEOs in the face of profit downturns, it is high-priced firms that are less likely to oust their CEOs. That is, once I control for stock price, the effects of institutional ownership on firms' R&D policies and CEO firing disappear, suggesting that the property of institutional ownership mitigating short-termism identified in the extant literature is largely derived from its correlation with stock price level.

Of course, with additional information, such as portfolio turnover and momentum trading suggested by Bushee (1998), one can classify institutions into long-term investors and short-term investors. One can also similarly classify individual investors into the two groups. In general, long-term investors are more likely to stick by the firm when temporary setbacks in the innovation process occur, allowing firms to pursue R&D projects that have high rewards and also high risk of failure. My findings imply that firms keeping higher stock price levels tend to attract more long-term investors, and that having higher institutional ownership is a mixed bag in which short-term institutional investors' interest in short-term

profits appears to offset the contributions of long-term institutional investors, making institutional ownership as a whole ineffective in enhancing innovation.

To analyze firm innovation, I follow Aghion et al. (2013) and use future citations of a firm's patents to measure its innovation (or productivity of R&D investments). Based on U.S. firms with patent data available from 1980 to 2005, I find that high-priced firms have more innovation than low-priced firms, and that the effect of institutional ownership on innovation largely disappears in the presence of share price. The regressions estimates suggest that a doubling in the share price level (e.g., from $20 per share to $40 per share) during year *t* is associated with a 17.5% increase in the total citation-weighted number of patents during year *t+2*, controlling for other firm characteristics. In terms of one standard deviation increase in stock price level, the corresponding increase in future innovation is 12%. The numbers suggest that the effect of stock price level on fostering innovation is nontrivial.

I further identify the channel through which stock price level affects innovation.[2] Specifically, I find that a high stock price level strengthens the relationship between innovation inputs (i.e., R&D capital) and innovation outputs (i.e., patent citations). In other words, firms investing more in R&D benefit more in innovation by setting high stock price level; but, it does not benefit much to those firms that invest little in R&D. The findings suggest that, by mitigating investor short-termism, high stock price levels improve the productivity of R&D investments.

It is possible that, anticipating more future innovation by some firms, investors bid up their stock prices. In this case, it is innovation causing high stock price, rather than high stock price enhancing innovation. However, firms can decide to keep high stock price levels or

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[2] While investing in R&D is a very important factor in pursuing innovation, firms can also acquire innovation through mergers and acquisitions or through buying patents from other firms.

split their stocks to automatically lower their stock price levels. In fact, according to Weld et al. (2009), many firms split their stocks to manage their stock price levels and, consequently, the average price for a share of stock on the NYSE has remained roughly constant at about $35 since the Great Depression. My hypothesis emphasizes that innovative firms are more likely to keep their stock price at higher levels to mitigate investor short-termism. Thus, to further verify the findings, I do two robustness checks. First, I investigate a sample of firms that split their stocks. If my hypothesis is correct we expect that (i) innovative firms are less likely to engage in stock splits, and (ii) if they do, innovation would decline following the falls in stock price levels induced by stock splits. Consistent with these predictions, I find that the likelihood of engaging in a stock split is lower for more innovative firms. Also, although stock splits tend to attract more institutional investors (see Lin, Singh, and Yu, 2009; Chemmanur, Hu, and Huang, 2014), I also find that innovation tends to decline following stock splits, and declines more for firms that choose a larger split factor.

For the second robustness check, I examine a sample of IPO firms in which managers set offering price ranges to sell shares to institutional investors as well as retail investors before their shares traded on exchanges. My hypothesis predicts that, holding other things constant, IPO firms that set higher offering prices (based on the midpoint of the offering price range) would have more future innovation. Indeed, the results show that innovation increases with IPO firms' offering price levels, not institutional ownership.

In sum, the findings suggest that high stock price levels have a function of mitigating investor short-termism. This function helps managers to preserve an environment for promoting innovation. The findings also suggest that while many firms choose to split their

stocks, innovative firms keep their stock price at a high level to curtail speculative trading. In other words, firms' stock price levels play an important role in the governance of innovation.

The remainder of the Dissertation is organized as follows. Chapter 2 reviews related literature. Chapter 3 describes sample selection, variable measures and descriptive statistics. Chapter 4 compares institutional ownership and stock price levels in mitigating short-termism. Chapter 5 investigates the effects of stock price level and institutional ownership on firm innovation. Chapter 6 presents two robustness checks to further verify the findings. Chapter 7 concludes the Dissertation.

CHAPTER 2: LITERATURE REVIEW

In this chapter, I first review the literature on governance mechanisms to foster innovation and survey studies on the role of institutional ownership in the governance of innovation. I also review studies on the information content of stock price level, and develop hypothesis to show that, like institutional ownership, stock price level can serve as a governance mechanism to enhance innovation.

2.1. Governance of Innovation

The literature on the governance of innovation has centered around three areas, namely (i) incentive contracts, (ii) external governance channels, and (iii) ownership structures.

The first governance mechanism is through incentive contracts. Manso (2011) models the incentives for innovation through the trade-off between exploration of new untested ideas and exploitation of well-known ideas. He shows that since exploration of new untested ideas, which bring about innovative products, involves uncertainty and is likely to fail, the optimal incentive contract that motivates this innovative process needs to exhibit substantial tolerance for short-term failure and reward for long-term success. Even though the prediction from Manso's (2011) model has received supportive evidence from empirical studies (see, Tian and Wang, 2014; Ederer and Manso, 2013; and Azoulay, Zivin, and Manso, 2011), designing incentive contracts to effectively stimulate innovation is "particularly demanding" (Holmstrom 1989) and might not be a good solution (Francis and Smith 1995) due to the high agency cost and contracting costs stemmed from the nature of the innovation process.

The second governance mechanism for innovation is through mergers and acquisitions. The theoretical literature has provided two opposite predictions on the effects of takeover threats on firm innovation. On one hand, takeover pressures discipline managers and force them to take value-enhancing projects (Jensen, 1988). The prediction from this line of argument is that, if more anti-takeover mechanisms are available, there will be managerial entrenchment (the "quiet life" effect) and therefore, a reduction in innovation. On the other hand, Stein (1998) shows that, under asymmetric information between firm managers and stock holders, takeover pressures give managers incentives to focus on short-term earnings and forego long-term projects. This is because poor short-term earnings may cause the stocks to be underpriced, thus becoming good targets for takeovers. The managerial myopia induced by takeover threats, therefore, impedes innovation (the "managerial myopia" effect.)[3]

In testing the predictions from theoretical models, the literature has focused on the effects on innovation caused by the adoption of anti-takeover provisions at firm level and at the state level (anti-takeover laws.) At the firm level, Meulbroek, Mitchell, Mulherin, Netter, and Poulsen (1990) find that firms reduced their R&D intensity after adopting anti-takeover provisions. This finding implies that, instead of reducing managerial myopia as predicted by Stein's model, anti-takeover provisions have lead to managerial slack that is detrimental for innovation. Using patent activities to proxy for firm innovation, Becker-Blease (2011) and Chemmanur and Tian (2013), however, find that firms with larger number of takeover provisions adopted (i.e., higher G-index) have higher numbers of patents and patent citations

[3] Shleifer and Summers (1998) also come to the same conclusion that anti-takeover stimulates innovation. The reason is that anti-takeover facilitates long term contracting with the managers.

in the future, suggesting that protection from these anti-takeover provisions reduces managerial myopia and stimulates innovation.[4]

At the regulatory level, Atanassov (2012) shows that during the 4-year period after a state passes a Business Combination anti-takeover law, firms incorporated in that state reduce their innovation (measured by citations per patent) by 21% relative to similar firms incorporated in the states that do not pass the law. Sapra, Subramanian, and Subramanian (2013) model the trade-off between expected takeover premium and expected loss of private benefit of control in the case of takeover. When there are little (high) takeover pressures, both takeover premium and loss of private control are low (high). Under these circumstances, firms will take innovative projects because either the expected payoff from innovative projects is higher or expected takeover premium is higher for innovative firms. Consistent with the model, they find a U-shape effect of the strength of antitakeover law on innovation. Specifically, firms are more innovative when antitakeover laws are weak (small state-level antitakeover law index) or really effective (high antitakeover law index.) [5, 6]

Another external governance mechanism is product market competition. There has also been a long debate on how product market competition would affect innovation. The first strand of literature (the "Schumpeterian view") argues that higher product market competition stifles innovation because it reduces the post-innovation profits, giving disincentives for new entrants and, therefore, reducing innovation (Schumpeter 1942). The "escape-competition" view, however, comes to an opposite conclusion. Under this view,

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[4] See Gompers et al. (2003) for a description of the G-index

[5] See Bebchuk and Cohen (2003) for a description of the state-level anti-takeover law index.

[6] In a recent paper, Bena and Li (2014) examine how M&A activities are shaped by firm innovation characteristics. They find that one driver for M&As is the synergies obtained from the combination of the acquirers, which tend to hold large patent portfolio and low R&D, and targets, which tend to have high R&Ds and slow growth patent portfolio.

product market competition is an incentive mechanism that forces managers to innovate because the profits from being a leader in a neck-and-neck industry will be higher (Aghion et al. 2005). Empirical evidence on the relationship between product market competition and innovation is also inconclusive (see Cohen and Levin (1992) for a thorough review of the empirical evidence before 1990s and Correa and Ornaghi (2014) and Le and Vo (2014) for a more recent literature review).

In sum, various theories concerning the effects of external corporate governance mechanisms on innovation have been proposed in the literature and they often have opposite views in terms of enhancing or impeding innovation. These conflicting views suggest that the external governance mechanisms tend to have side effects, which may explain why collective empirical evidence on the effectiveness of the external governance mechanisms on innovation tends to be mixed.

Finally, shareholder structure is also an important factor in the governance of innovation. Francis and Smith (1995) examine the role of management holdings and outside block holdings on innovation and find that, due to the less effective monitoring from diffused shareholdings, diffuse-ownership firms are less innovative than firms with either a high management ownership or large equity block holders. Through a different mechanism, Edmans (2009) show that large block holdings foster innovation. This is because block holders have more incentive to gather information and get informed about the firm. Therefore, their trading makes share prices to reflect fundamental value rather than short-term earnings. This encourages managers to invest in long term projects and, therefore, stimulate innovation.

Complementary to Edmans's (2009) finding, Aghion et al. (2013) examine the role of shareholdings from institutional investors and find that institutional ownership (IO) fosters innovation. The empirical evidence from Aghion et al. (2013) suggests that the positive effect of IO on innovation does not come from the more effective monitoring from institutional investors that forces managers to innovate, as predicted by the "lazy manager" hypothesis. Rather, similar to Edmans (2009), it comes from the institutional investors' sophisticated knowledge that allows them to access the outcome of innovation projects better, therefore assuring jobs for managers in the event of idiosyncratic failures ("career concern" hypothesis).[7]

Consistent with the institutional investors' sophistication hypothesis, Bushee (1998) shows that firms with high institutional ownership are less likely to cut R&D to reverse a decline in earnings. However, Bushee (1998) also finds that firms with a large holding by institutional momentum traders with high portfolio turnovers ("transient investors") tends to increase the probability of reducing R&D investments to meet short term earnings. This evidence suggests that the pressure caused by the trading from transient investors leads to managerial myopic investment behavior.

Besides the roles of institutional investors in the governance of innovation, Luong, Moshirian, Nguyen, Tian, and Zhang (2014) and Bena, Ferreira, and Matos (2014) examine the roles of <u>foreign</u> institutional investors on innovation. Both studies show that foreign institutional investors foster innovation through their monitoring and job assurance to the managers.[8]

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[7] See Appendix B for a more detail review on Aghion et al.'s (2013) tests.

[8] Public or private equity structure also has impact on innovation. Private equity ownership allows firms to pursue exploration of new ideas (instead of exploitation of conventional ideas), leading to higher innovation

Overall, the extant literature shows that institutional ownership in general has significant positive impacts on firm innovation. However, this inference has one drawback. That is, managers are assumed to play a passive role as if they do not have a full control of corporate strategies since they need to be "monitored" and/or "assured" by institutional investors in order to pursue innovation. Consequently, I question the inference and propose an alternative hypothesis about share price level to explain why institutional ownership may appear to have positive effects on corporate innovation.

2.2. Share Price Level

Stock prices of publicly traded firms are initially set by managers when firms go for IPOs. After IPOs, stock prices can fluctuate based on expectation about firms' cash flows and by managers' decision to split shares, a process involving a change in the total number of shares outstanding and a corresponding change in the share price level. There has been little research on the level of offering price at firm IPOs. One exception is Fernando, Krishnamurthy, and Spindt (2004) who show that IPO share price levels increase with the reputation of the underwriters of the IPO firms. Besides, they show that IPO share price level is positively correlated with institutional ownership after the IPO, suggesting that managers may set a higher share price level to attract institutional investors.[9]

On the other hand, there has been a large body of literature on stock splits, one common corporate event over the last several decades. The first hypothesis is that firms conduct stock splits to move their share price to a "normal trading range" that helps increase

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(Ferreira, Manso, and Silva 2012). Similarly, Lerner, Sorensen, and Stromberg (2011) show that firms become more innovative after being acquired by private equity fund (public-to-private transition).

[9] Fernando et al. (2004) discuss in details the restrictions to "penny stocks" set by stock exchanges that could affect managers' choice of IPO offering price.

the marketability of the shares and, therefore, increase firm investor base. This hypothesis is in line with Merton's (1987) incomplete information model and has received supporting evidence (see, e.g. Barker (1956), Lamoureux and Poon (1987), Mukherji, Kim, and Walker (1997), and Dyl and Elliott (2006) for evidence on enlarged investor base after stock splits; and Dolley (1933) and Baker and Gallagher (1980) for surveys on CEOs about motives for splits). The hypothesis, however, fails to explain why the average share price level has been around $35 after the Great Depression (Weld et al. 2009) despite changes in incomes, inflations, and investor structure on the stock market over the same period.

The second hypothesis is that managers use stock splits to convey private information to investors, signaling that they have a strong future performance prospect to support the lower post-split price level ("signaling" hypothesis). Consistent with this hypothesis, Grinblatt, Masulis, and Titman (1984) examine a sample of splitting firms without other concurrent announcements and find that there are significantly positive announcement returns and also significant abnormal returns in the months subsequent to the stock announcement. Similar evidence is reported in other studies, for example, Asquith, Healy, and Palepu (1989), McNichols and Dravid (1990), and Ikenberry, Rankine, and Stice (1996). Chemmanur et al. (2012) show that splits do facilitate information production and therefore reduce information asymmetry between firms and investors However, Byun and Rozeff (2003) and Lakonishok and Lev (1987) find a non-abnormal post-split firm performance. Also, Easley, O'Hara, and Saar (2001) find that information asymmetry does not decline after stock splits even though splits attract more uninformed traders. This contradicting evidence suggests that both signaling hypothesis and normal trading range hypothesis cannot satisfactorily explain stock splits.

There are other studies that offer different explanations on why firms choose to have their shares traded at some particular level. Consistent with evidence in Fernando et al. (2004) about IPO offering price, Dyl and Elliott (2006) provide evidence that managers set higher share price to attract larger investors, and lower share price to attract small or individual investors. Baker, Greenwood, and Wurgler (2009) argue that managers make decisions on nominal share price level by responding to changes in investors' demand on shares with different price levels. Using the difference in the average market-to-book ratio of low-priced and high-priced firms to capture low-price premium, they show that firms are likely to split shares or set lower IPO offering price when the low-price premium is high. On the other hand, Brennan and Hughes (1991) links share price level with the supply of information. In their model, firms will conduct stock splits to facilitate information production about the firms. The information production is done through brokers whose commissions are based on share price, a factor that managers have control over. Consistent with this hypothesis, they show that the number of analysts following a firm is inversely related to share price level. Fernando, Gatchev, and Spindt (2012) also present similar evidence on the negative relationship of share price and analysts following. Fernando et al. (2012) additionally show that firms with more benefits from institutional monitoring relative to benefits from analyst coverage will set higher share price level. Recently, Chan, Li, Lin, and Lin (2013) examine the reasons for firms to set high share price level. They show that high stock price levels impede informed trading on the stocks and reduce price informativeness. Based on this evidence, they suggest that firms keep their share prices at high levels when they need less feedback from stock the market.

Overall, despite the large body of literature on share price levels in general and stock splits in particular, there is still no clear answer to the questions of why share price matters to investors, why firms split their shares, and why managers appear to manage the trading price level of their shares on the stock markets. The nominal share price after all remains a "puzzle". [10]

2.3. Institutional Investor's Preference of High Price Shares

Kumar (2009) show that small-priced stocks have "lottery" features in that they require very small investment for each share, and they have small possibility of getting very high return in the future. For this reason, low-priced shares with lottery features attract retail investors who like to "gamble" the stock market. Related to Kumar's (2009) evidence of the retail investors' preference on low-priced stocks, institutional investors have been well-known for their preference in high-priced stocks and avoidance of low-priced stocks. The first reason is because institutional investors, as fiduciaries, may face restrictions on the types of shares they can invest in ("prudent-man law"). Del Guercio (1996) investigates the restrictions from this law for different types of institutional investors (banks, pension funds, mutual funds) and finds that banks do follow the law, meaning that they invest in high quality stocks. Badrinath, Gay, and Kale (1989) also show evidence of prudence investment of non-banks institutions. Second, institutional investors are not financially constrained as individual investors, so they can afford high-priced shares with a large number of shares. Gompers and Metrick (2001) provide evidence that institutional investors invest significantly more in high price stocks. So overall, there appears to be a strong positive relationship between share price level and institutional ownership.

[10] See Weld et al. (2009) for a more complete review on share price "puzzle".

CHAPTER 3: SAMPLE SELECTION, VARIABLES MEASURES AND DESCRIPTIVE STATISTICS

3.1. Sample Selection and Variable Measures

The paper data samples come from several sources. I first start with Compustat annual file. Following the literature, I construct the following key variables for my analyses. First, I use share price at fiscal yearend (PRCC_F) to proxy for share price level.[11] Next, I use log(SALES) to proxy for firm size; and calculate R&D stock (RDC) as R&D capital depreciated at 20% rate per year (Chan, Lakonishok, and Sougiannis, 2001). Specifically, for each year t,

$$RDC_t = R\&D_t + 0.8*R\&D_{t-1} + 0.6*R\&D_{t-2} + 0.4*R\&D_{t-3} + 0.2 * R\&D_{t-4}$$

where $R\&D_t$ is R&D expenditure in year t.[12] Also, I measure Capital-labor ratio (K/L) as Net Property, Plant, and Equipment PPENT scaled by number of employees EMP. Definitions of other variables used in the paper are presented in Appendix A, which include Market-to-Book ratio, Tobin's Q, Dividends payment, S&P500 index membership, and Tangibility. I eliminate observations with stock price at fiscal yearend (PRCC_F) of less than $5 because such low-priced firms are usually distressed and not attractive to institutional investors. Following the literature I also exclude financial (SIC codes 6000s) and utilities firms (SIC codes 4900s) because firms in these industries must follow some specific regulations, which do not apply to all other firms. Observations from non-US firms (FIC is not "USA"), with total assets (AT) of less than $1m, or missing values in SALES or capital labor K/L ratio are also excluded.

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[11] For robustness checks I use average trading price calculated from CRSP. The results are qualitatively the same.

[12] In order to keep firms with zero RDC in the later analyses that use the logarithm of RDC, I add 1 to the originally calculated RDC value.

I use patent citations from the NBER patent database, updated to 2006, to proxy for firm innovation.[13] According to Hall, Jaffe, and Trajtenberg (2001 and 2005), there is a lag about two years between a patent's application date and its grant date. Hence, following the literature, I focus on a firm's patent applications that had ultimately been granted, weighted by the number of future citations, to measure its innovation. To address the truncation issue with the citations data I adjust the number of citations by the adjustment factor, HJTWT, provided in the NBER patent database.[14] This future citations weighted patent measure, which reflects the productivity of innovation, has certain advantages. First, unlike R&D, which is innovative inputs and involves uncertainty, patents are realized technologies that could affect future operating performance. Second, patents measure the efficiency of innovation process and are publicly traded. Third, patents are a powerful tool for firms to maintain competitive advantages. Finally, firms can receive incomes from patent royalties.

I obtain institutional holding data from Thomson Financial CDA/Spectrum 13F filings for all ordinary common stocks traded on NYSE, AMEX, and National Association of Securities Dealers Automated Quotations (NASDAQ). I follow Campbell, Ramadorai, and Schwartz (2009) to clean this database. In my calculation, there are about 6% of quarter-stock-institution duplicated observations. I keep only the report of latest filing date (FDATE) for each report date. For firms with no reports from the database, I record their institutional holding as zero. For those with over 100% owned by institutional investors, I set the holding to missing to avoid the possibility of data errors.

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[13] The data set is downloadable from https://sites.google.com/site/patentdataproject/Home

[14] A patent may receive citations many years after its grant date. However, the patent citation information for our sample firms is observed only up to 2006. For this reason, newer patents are more subject to the citation truncation issue. See Hall et al. (2001, 2005) for more discussion of this issue and their method used to calculate the truncation adjustment factor (HJTWT).

I collect stock prices, returns, trading volume, and number of shares outstanding from the Center for Research in Security Prices (CRSP) monthly tapes for all common stocks (CRSP share code 10 and 11) traded in NYSE, AMEX, and NASDAQ. Then, I compute a firm's stock price level by averaging monthly closing prices in a year; its share turnover as the average of monthly share turnovers; and its price volatility using monthly stock returns over previous two years. I also identify firms that split their shares through CRSP event tape. Split firms are those that have distribution codes (DISTCD) of 5523 or 5533, have non-missing split declaration date, and have a split factor (FACSHR) of at least 0.25.

In my tests on IPO firms I collect IPO price from Thomson Financial SDC database. Specifically I collect IPO actual offering price or mid-point filing range from IPO initial filings. The IPO price is then merged with patents and Compustat samples based on firm CUSIP and IPO year.

Finally, I use Aghion et al.'s (2013) data for out tests on CEO turnovers.[15] According to Aghion et al, the CEO turnover data are constructed by Fisman, Khurana, and Rhodes-Kropf (2005). The whole data set, along with share price level from my sample, is also used as a robustness check for some of my other analyses.

My final main sample starts from 1980, the first year with available institutional ownership data, and ends at 2005, one year before the final year of available patent data. The sample includes 58,635 firm-year observations from 8,759 unique firms that have valid future patent data.[16]

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[15] I thank Aghion et al. (2013) for making their complete dataset and programming codes available online at http://www.aeaweb.org/articles.php?doi=10.1257/aer.103.1.277

[16] Analyses that require lag or variables other than Sales and K/L will be based on smaller samples depending on data availability.

3.2. Descriptive Statistics

Table 1 reports the descriptive statistics of my firms in the main sample. As shown in Panel A of Table 1, the mean and the median stock price of the firms in my sample are $21.74 and $16.00, respectively. On average and on the median, institutional investors own 35% and 33% of the sample firms' outstanding shares, respectively. As shown in Panel B, a firm's institutional ownership is highly correlated with its stock price level, with an average correlation of about 0.47 in annual cross-sectional correlations, which indicates that institutions tend to have higher ownership in firms with higher stock prices, consistent with Gompers and Metrick's (2001) findings. This high correlation is the starting point to contend that some of institutional ownership's properties in the governance of firm innovation may derive from its correlation with stock price level.

Indeed, both institutional ownership and stock price level are correlated to firm innovation, measured by total annual citations on a firm's patents. While the average correlation between institutional ownership and firm innovation is 0.236, the average correlation between natural log of stock price level and firm innovation is higher at 0.321.

Of course, many factors may contribute to firm innovation. For example, a firm's R&D capital is a significant contributor to innovation, with an average correlation of 0.696 between the two variables. Firm size, as measured by annual sales, is also a significant factor, having an average correlation of 0.344 with innovation. A firm's capital-to-labor ratio also has some effect on its innovation, with an average correlation of 0.119. Furthermore, a firm's innovation should have a positive effect on firm valuation, which may be captured by its Tobin's Q. On average, the correlation between Tobin's Q and firm innovation is 0.104. In the sections that follow, I follow Aghion et al. (2013) to control for these factors in

comparing the roles of institutional ownership and stock price level in the governance of innovation.

Table 1: Sample Statistics

This table shows characteristics of firms included in the sample. Sample includes domestic non-financial firms from CRSP/Compustat intersection from 1980-2005. Variable definitions are in Appendix A. All variables except CITES, Price, and IO are trimmed at 1% and 99%; IO is trimmed at 100%. Firm-year observations with negative book equity value, total assets less than $1m, stock price less than $5, or having missing values of Price, Sale, or K/L are excluded. Panel A reports statistics for the whole sample; Panel B reports correlation of key (transformed) variables; Panel C reports variables mean values for sub-samples based on share price quartiles; and Panel D reports mean values for sub-samples based on institutional ownership quartiles.

Panel A: Whole sample

Variables	N	Mean	S.D	Median
Cites	58635	180.43	1520.99	0
P	58635	21.74	27.1	16
IO	58635	0.35	0.24	0.33
K/L	58635	123.6	340.28	43.48
SALES	58635	5.27	1.87	5.09
RDC	42191	118.96	789.87	0.34
Q	58028	1.99	1.52	1.46
M/B	57275	2.86	3	1.93
R9	50641	0.17	0.48	0.09
R3	56546	0.06	0.25	0.03
Dividends	58300	0.01	0.02	0
Age	58628	15.55	15.49	11
Turnover	56797	0.1	0.11	0.06
Volatility	48666	0.13	0.06	0.12
S&P500	58635	0.14	0.35	0

Panel B: Main Variables Correlation

	Ln(1+CITES)	Ln(1+Counts)	Ln(P)	IO	Ln(K/L)	Ln(Sales)	Ln(RDC)
Ln(1+CITES)	1.000						
Ln(1+Counts)	0.943	1.000					
Ln(P)	0.321	0.354	1.000				
IO	0.236	0.270	0.471	1.000			
Ln(K/L)	0.119	0.157	0.169	0.212	1.000		
Ln(Sales)	0.344	0.413	0.577	0.552	0.156	1.000	
Ln(RDC)	0.696	0.742	0.293	0.303	0.162	0.324	1.000
Q	0.104	0.095	0.206	0.103	0.005	(0.155)	0.175

Table 1 (cont.)

Panel C: Sample statistics by Price Quartiles

Quartile	Low Price	(2)	(3)	High Price
CITES	21.93	47.87	96.03	557.23
COUNTS	1.49	3.21	5.85	32.45
P	7.01	12.54	21.19	46.34
IO	0.20	0.30	0.41	0.51
K/L	106.25	111.78	128.61	147.90
SALES	3.97	4.74	5.53	6.83
RDC	20.81	36.39	55.78	311.64
Q	1.76	1.82	2.04	2.34
M/B	2.47	2.53	2.87	3.57
R9	0.07	0.14	0.20	0.25
R3	0.01	0.04	0.07	0.10
Dividends	0.01	0.01	0.01	0.02
Age	10.49	12.29	15.27	24.19
Turnover	0.09	0.10	0.11	0.11
Volatility	0.16	0.14	0.12	0.10
S&P500	0.02	0.04	0.11	0.39
N	14736	14627	14646	14626

Panel D: Sample statistics by Institutional Ownership Quartiles

	Low IO	(2)	(3)	High IO
CITES	18.31	100.11	290.24	313.13
COUNTS	1.03	6.67	16.51	18.71
P	13.15	17.03	23.79	33.01
IO	0.09	0.25	0.43	0.65
K/L	116.12	116.29	129.90	132.10
SALES	3.83	4.82	5.79	6.63
RDC	14.34	88.27	179.57	159.70
Q	2.25	1.93	1.86	1.92
M/B	3.38	2.71	2.62	2.75
R9	0.21	0.14	0.15	0.18
R3	0.06	0.05	0.05	0.07
Dividends	0.01	0.01	0.01	0.02
Age	10.28	12.62	17.82	21.47
Turnover	0.09	0.10	0.11	0.12
Volatility	0.15	0.14	0.12	0.11
S&P500	0.00	0.04	0.17	0.34
N	14664	14656	14655	14660

Panel C of Table 1 reports the mean values of the key variables for each price quartile. The cut-offs for each quartile are determined by the cross-sectional distribution of stock price in each year. The mean stock prices for the highest price quartile is $46.34, which is more than 6 times as high as the mean stock price of $7.01 for the lowest price quartile. On average, institutional investors own around 20% of the firms' outstanding shares in the lowest price group; it increases to 30% and 41% for the next two price quartiles, and rises up to 51% in the highest price group. This positive correlation is consistent with Dyl and Elliott's (2006) findings. Also consistent with their findings is the positive correlation between firm size and stock price level.

Interestingly, on average, higher-priced firms also have more R&D investments and more innovation. For the firms in the lowest price quartile, the average total patents applied (and subsequently granted) each year is only 1.49 while the corresponding number in the highest price quartile is 32.45. The average citation weighted patents are about 22 and 557 for the lowest and highest price quartiles, respectively. These statistics provide initial evidence consistent with the paper's hypothesis that innovative firms choose high stock price levels to guard against investor short-termism and to foster innovation.

In Panel D of Table 1 I similarly report the mean values of the key variables for each institutional ownership quartile. The cut-offs for each quartile are also determined cross-sectionally each year. The highest quartile has an average institutional ownership of 65% and an average stock price of 33.01. Hence, the firms that institutional investors most prefer have an average price of around $33, which is lower than the average price of around $46 for the firms in the highest price quartile. This suggests that while institutional ownership tends to

increases with stock price level, their preference toward high-priced firms declines when their stock price levels exceed some point.

To further illustrate this point, I extend Gompers and Metrick's (2001) analysis on what may attract institutional ownership. Table 2 presents the results of regressing institutional ownership on price, price squared, and a set of control variables, including firm size, book-to-market ratio, momentum, dividend, firm age, turnover, volatility and S&P 500 dummy. The results show that price is significantly positive, but price squared is significantly negative. This non-linear relationship between institutional ownership and stock price is consistent with the conjecture that institutions seem to change their preference toward high-priced firms beyond some price level.[17] This is an important difference between institutional ownership and stock price level when I try to differentiate the association of stock price with firm innovation from that of institutional ownership later on.

It is worth mentioning that, as shown in Panels C and D of Table 1, the firms in the highest price quartile have an average annual total patent citations of 557, which is higher than the average annual total citations of 313 for the firms in the highest institutional ownership quartile. This provides a hint that, on average, high-priced firms is more innovative than high-IO firms. It is also a preview of what this research attempts to show that high stock price level is more relevant to foster innovation than high institutional ownership.

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[17] The turning point of the institutional investors' preference for high-priced stocks suggested by the regression results is around $80.

Table 2: Institutional Ownership and Stock Price

This table presents coefficients estimates of the following regression:

$$IO = \beta_0 + \beta_1 \log(P) + \beta_2 \log(P) * \log(P) + \beta_3 X + \varepsilon$$

where P is share price level and X is a matrix of control variables. All variables are defined in Appendix A. Columns (1) and (2) present regression coefficients using Fama-MacBeth technique with Newey-West corrected standard error with lag length 2 and include industry fixed effects. Columns (3) and (4) present results using OLS regressions with robust firm cluster standard errors and a full set of year and industry dummies. Industries are defined as Compustat 3-digit SIC codes. Sample is from 1980 to 2005. Standard errors are reported in parentheses; *, **, *** denotes statistical significance at 10%, 5%, and 1%, respectively.

	(1) FM	(2) FM	(3) OLS	(4) OLS
Log(P)	0.085***	0.240***	0.085***	0.272***
	(0.004)	(0.036)	(0.005)	(0.018)
Log(P)^2		-0.026***		-0.031***
		(0.006)		(0.003)
Log(B/M)	-0.002	-0.000	0.007*	0.009***
	(0.006)	(0.007)	(0.004)	(0.003)
Firm Size	0.050***	0.049***	0.053***	0.052***
	(0.003)	(0.003)	(0.002)	(0.002)
Momentum (-12,-3)	-0.023***	-0.025***	-0.015***	-0.017***
	(0.005)	(0.005)	(0.002)	(0.002)
Momentum (-3,0)	-0.028***	-0.029***	-0.017***	-0.018***
	(0.005)	(0.005)	(0.004)	(0.004)
Log(Div/Me)	-0.588***	-0.714***	-0.424***	-0.585***
	(0.206)	(0.214)	(0.125)	(0.124)
Log(Firm Age)	-0.002	-0.001	-0.008***	-0.007**
	(0.004)	(0.003)	(0.003)	(0.003)
Log(Share Turnover)	60.942***	59.081***	52.001***	49.977***
	(5.621)	(5.270)	(2.238)	(2.161)
Log(Volatility)	-0.566***	-0.524***	-0.516***	-0.482***
	(0.057)	(0.058)	(0.039)	(0.037)
S&P500	-0.024	-0.012	-0.025***	-0.013*
	(0.020)	(0.018)	(0.007)	(0.007)
Year FE			Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	44165	44165	44165	44165
R^2	0.577	0.584	0.578	0.585

CHAPTER 4: MITIGATING INVESTOR SHORT-TERMISM

Investor short-termism would push managers to excessively focus on quarterly earnings performance at the expense of long-term potentials, which would be unfavorable to R&D. My hypothesis posits that keeping high stock price levels allows firms to mitigate investor short-termism and enhance innovation. This chapter compares the effectiveness of stock price (P) and that of institutional ownership (IO) in mitigating investor short-termism. Chapter 5 then compares their associations with firm innovation.

4.1. R&D Policy

Bushee (1998) examines the role of institutional ownership in managers' decision to reduce R&D spending that could reverse a decline in earnings. He finds that managers are less likely to cut R&D to reverse an earnings decline in firms with high institutional ownership. His finding suggests that institutional investors play an important role in mitigating managers' myopia.

I re-run Bushee's (1998) analysis to see whether it is high institutional ownership or high price that has an effect of reducing pressure on managers to cut R&D to boost operating performance. Following Bushee (1998), I select firms that have a decline in pre-tax, pre-R&D earnings in the current year but could potentially reverse the earnings decline by cutting R&D (i.e., the decline in earnings is less than the R&D expenditure of the previous year). To be consistent with Bushee (1998), I include firms with all price levels and exclude firms with R&D/Sales of less than 1% and in 3-digit SIC industries with fewer than 3 firms. I then estimate the effect of share price level on R&D cutting decision by using the Probit regression model:

$$\Pr(RDCUT_{i,t} = 1) = \Phi(\beta_0 + \beta_1 \log(P)_{i,t} + \beta_2 X_{i,t} + \beta_3 Industry\_DM + \beta_4 Year\_DM + \varepsilon_t) \quad (1)$$

where $\Phi(\cdot)$ is the cumulative Gaussian distribution, RDCUT is a dummy variable that takes the value of 1 for firms that make smaller investments in R&D in the current year compared to that of the last year and 0 otherwise, X is the set of control variables as defined in Bushee (1998), and subscripts i and t denote firm and time indicators. Table 3 reports the Probit regression results.[18]

Model (1) reports the results based on Bushee's (1998) sample period from 1983 through 1994. It shows that, without P, institutional ownership is significantly negative, which is consistent with Bushee's finding that firms with higher IO are less likely to cut R&D following poor earnings performance. However, adding P to the Probit regression model makes IO insignificant, as shown in model (2). Instead, P is significantly negative, suggesting that, following poor earnings, high-priced firms, not those with more IO, are less likely to cut R&D.

Model (3) shows that the results hold for the main sample period from 1980 through 2005. The results still hold when I restrict the sample firms to have stock price more than \$5 and total assets more than \$1 million, as reported in Model (4). Furthermore, since firms' decisions on R&D investments may be affected by industry characteristics or macroeconomics conditions (Brown, Fazzari, and Petersen 2009), for robustness checks, I control for year-fixed effects in model (5) and control for both year-fixed and industry-fixed effects in model (6). Both models show that the effect of stock price level remains almost the same as in model (3).

[18] The results are almost identical if I use logit regressions.

Table 3: R&D Cut to Reverse Earning Declines

This table reports Probit regression of R&D cutting indicator on a set of independent variables following Bushee (1998). Sample includes firms with a change in pre-tax, pre-R&D earnings is negative but larger than previous year's R&D expenditure. Variable definitions are in Table 1. Columns (1) and (2) are based on Bushee's (1998) original sample period (1983-1994) while the next four columns (3) – (6) on full sample period (1980 – 2005). Standard errors are reported in parentheses; *, **, *** denotes statistical significance at 10%, 5%, and 1%, respectively.

Sample period	1983-1994		1980 – 2005			
	(1)	(2)	(3)	(4)	(5)	(6)
IO	-0.398**	-0.305	0.090	0.014	-0.060	-0.061
	(0.201)	(0.199)	(0.108)	(0.119)	(0.113)	(0.115)
log(P)		-0.118***	-0.225***	-0.114**	-0.177***	-0.176***
		(0.040)	(0.025)	(0.044)	(0.028)	(0.029)
PCRD	-0.468***	-0.442***	-0.166***	-0.086	-0.155***	-0.159***
	(0.090)	(0.088)	(0.052)	(0.070)	(0.053)	(0.053)
CIRD	-1.024***	-0.981***	-0.883***	-1.076***	-0.823***	-0.702***
	(0.269)	(0.271)	(0.156)	(0.195)	(0.169)	(0.175)
Q	-0.039*	-0.030	-0.024*	-0.020	-0.030**	-0.023*
	(0.024)	(0.022)	(0.013)	(0.016)	(0.013)	(0.013)
CCAPX	-0.249***	-0.244***	-0.304***	-0.296***	-0.299***	-0.298***
	(0.037)	(0.037)	(0.023)	(0.033)	(0.024)	(0.024)
CSALES	-0.219***	-0.216***	-0.143***	-0.183***	-0.140***	-0.152***
	(0.071)	(0.063)	(0.037)	(0.059)	(0.038)	(0.038)
MELOG	-0.057***	-0.009	0.019	0.010	-0.005	-0.006
	(0.021)	(0.026)	(0.016)	(0.019)	(0.017)	(0.017)
DIST	0.835***	0.843***	0.028	-0.036	0.020	0.040
	(0.074)	(0.085)	(0.061)	(0.075)	(0.061)	(0.062)
LEVB	0.233	0.188	-0.041	-0.030	0.012	0.039
	(0.147)	(0.150)	(0.091)	(0.121)	(0.092)	(0.094)
CFAT	-0.245	-0.082	-0.109	-0.042	-0.066	-0.126
	(0.152)	(0.158)	(0.088)	(0.125)	(0.089)	(0.093)
N	2788	2788	6032	4034	6032	6020
Conditions				Price >$5, AT>$1m	Year dummies	Year & Industry

In model (3), the coefficient of log(P) is -0.225 (t-value=-9.00). One can use this estimated beta of log(P), $\hat{\beta}_1$, to infer the marginal effect of stock price in reducing the probability of cutting R&D.[19] At the mean values of the other explanatory variables, the effect of a price increase from the 25th percentile to the 50th percentile leads to a 7.2% decline in probability of cutting R&D; and the effect of a price rise from the 50th percentile to the 75th percentile level leads to a 6.7% decline in probability of cutting R&D. These inferences suggest that the effect of stock price level on the R&D policy is non-trivial.

In sum, the findings suggest that the R&D policies of firms keeping higher stock price levels tend to be less affected by short-term earnings fluctuations. The evidence implies that high-priced firms tend to have long-term views on their R&D investments, consistent with the hypothesis that firms set high stock price levels to mitigate investor short-termism. The evidence also implies that, in the presence of stock price level, institutional ownership appears to play an insignificant role in reshaping managerial myopia.

4.2. Stock Price and CEO Turnovers

I next re-examine Aghion et al.'s (2013) finding that firms with higher IO are less likely to fire their CEOs in the face of profit downturns. For this test I rely on Aghion et al.'s (2013) dataset and compliment it with share price level from the sample. Table 4 replicates their analyses on the likelihood of forcing CEOs to resign, and then adds P and PxdE, the interaction of P and changes in earnings, to the explanatory variables. Consistent with

[19] As an example, I use the regression result from model (3) to calculate the marginal effect, which equals to $f(\overline{\mathrm{X}}\hat{\beta})\hat{\beta}$, where *f* is a normal density function and $\overline{\mathrm{X}}$ are a set of mean values of independent variables. In the sample of the R&D cutting test, the log(P) at the 25th percentile is 1.18, at the 50th percentile is 2.01, and at the 75th percentile is 2.82.

Aghion et al.'s (2013) findings, models (1) and (2) report that poor earnings increases the likelihood of CEOs being forced out but the likelihood of ousting CEOs because of poor earnings is reduced by IOs. Again, this effect from institutional ownership becomes insignificant once I add P and PxdE to their model. The evidence suggests that Aghion et al.'s (2013) finding that institutional investors are more tolerant to profit downturn and thus reduce mangers' career concerns in pursuing innovation is not robust. Instead, I find that even though the interaction term of price and changes in earnings, PxdE, is also insignificant, P is significantly negative, which implies that high-priced firms are less likely to force CEOs to resign than their low-priced counterparts.

Thus, while it is understandable that institutional investors have better incentives and higher capacity to monitor firm managers, it is questionable what the extant literature has shown concerning the effectiveness of IO on mitigating short-termism. The findings that P takes away from IO the explanatory power on firms' R&D policies and on CEO firing imply that the function of IO is largely derived from its correlation with P. Therefore, it is important to control for stock price levels when addressing the role of institutional ownership in the governance of innovation. Furthermore, the result reveals that high stock price levels have an important property of guarding against investor short-termism, allowing managers to pursue long-term projects.

Table 4: IO, Price, and CEO Turnovers

This table reports marginal effects of Probit regressions of forced CEO exits on firm profits and other determinants. Price is fiscal year end price of US Compustat firms. Dependent variable and all other independent variables data are from Aghion et al. (2013), downloadable from http://www.aeaweb.org/articles.php?doi=10.1257/aer.103.1.277. All regressions include a full set of time dummies and a quadratic in the tenure of the CEO. Refer to Aghion et al. (2013) for full variable description. Firm- cluster standard errors are reported in parentheses; *, **, *** denotes statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Log(P)		-0.013**		-0.013**
		(0.006)		(0.006)
Log(P) * Δ (Profits/assets)$_{t-1}$		0.129		0.173
		(0.271)		(0.251)
Δ (Profits/assets)$_{t-1}$	-1.604***	-1.691**	-1.274***	-1.594**
	(0.496)	(0.722)	(0.362)	(0.689)
IO $\times$ Δ (Profits/assets)$_{t-1}$	0.025**	0.017		
	(0.010)	(0.012)		
IO	-0.000	-0.000		
	(0.000)	(0.000)		
(IO > 25%) $\times$ Δ (Profits/assets)$_{t-1}$			1.057**	0.736
			(0.456)	(0.512)
IO > 25%			-0.033	-0.016
			(0.021)	(0.018)
N	1897	1771	1897	1771
Years	1988–1995	1988–1995	1988–1995	1988–1995

CHAPTER 5: INSTITUTIONAL OWNERSHIP, STOCK PRICE, AND FIRM INNOVATION

This chapter formally compares the associations of firm innovation with institutional ownership and stock price level. Following Aghion et al. (2013) and the extant literature on innovation, I regress firm innovation on institutional ownership (IO), stock price level (P), and a set of control variables (X) as follows:

$$\log(1+CITES_{i,t+2}) = \alpha + \beta_1 IO_{i,t} + \beta_2 \log(P_{i,t}) + \beta_3 X_{i,t} + Industry + Year + e \qquad (2)$$

The subscript t+2 under CITES indicates that I use patent citations two years into the future to measure innovation to capture the notion that it may take time for important patents to show their impacts.

For the control variables, I follow Aghion et al. (2013) to control for capital labor ratio (K/L), firm size, and R&D stocks. To control for growth opportunities, I include M/B or Tobin's Q. Since innovation might be different in different time periods and in different industries, I also include industry dummies as well as year dummies in all tests.

Furthermore, there are two factors that could lead to a positive association between future innovation and current stock price level. One factor is that, according to the dissertation's hypothesis, high stock price level mitigates investor short-termism and enhances innovation. And, the other one is that future innovation could be capitalized in current firm valuation and stock price is part of firm valuation. I include M/B or Tobin's Q in analysis to capture the valuation effect of innovation, which should allow me to more clearly test whether high stock price enhances innovation, as hypothesized in this research. Later, I provide several robustness tests to verify this inference.

5.1. Basic Results

Table 5 reports the results of OLS regressions with robust firm cluster standard errors. Consistent with Aghion et al.'s (2013) findings, in model (1), which controls only capital-to-labor ratio and firm size, institutional ownership is positive and significant. The regression coefficient on IO is 0.526 (t-value=5.21), very close to a marginal effect of institutional ownership on patents of around 6% with each 10% increase in IO, as reported by Aghion et al. (2013). However, in model (2) in which log(P) is added to help explain firm innovation, IO's coefficient declines to 0.12 (t-value=1.11). This result indicates that, in the presence of log(P), IO loses its power in explaining firm innovation.[20] In contrast, log(P) is very significant, with a coefficient of 0.396 (t-value=13.65).

Log(P) remains highly significant and IO insignificant in model (3), where I add R&D capital (RDC); in model (4), where I add M/B; and in model (5), where I add Tobin's Q. Given that RDC largely captures innovation inputs and patents are innovation output, it is not surprising that the regression coefficient on Log(RDC) is highly significant, ranging from 5.32 (t-value=26.60) in model (5) to 5.42 (t-value=27.10) in model (3). Further, adding Log(RDC) increases the regression R^2 from around 40% (model (2)) to 55% (models (3)-(5)). Models (4) and (5) show that innovation is significantly related to M/B and Tobin's Q, respectively. However, including M/B or Tobin's Q in analysis only slightly change the association between innovation and stock price level, suggesting that the association is more due to high stock price level fostering innovation and less due to the valuation effect of future innovation, as discussed above.

[20] I also re-run the analyses using Aghion et al.'s (2013) data and specifications and obtain virtually the same result, i.e., the effects of institutional ownership becomes statistically insignificant when I add into the model log(P). Details are presented in Appendix C.

Table 5: Share Price, Institutional Ownership and Innovation

This table presents OLS regressions of future innovation on firm characteristics:

$$\log(1+CITES_{i,t+2}) = \alpha + \beta_1 IO_{i,t} + \beta_2 \log(P_{i,t}) + \beta_3 X_{i,t} + Industry + Year + e$$

Variables definitions are in the Appendix A. All regressions include year and industry dummies. Industries are Compustat 3-digit SIC codes. Sample is from 1980 to 2005. Robust firm cluster standard errors are reported in parentheses; *, **, *** denotes statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Log(P)		0.396***	0.253***	0.211***	0.175***	0.017
		(0.029)	(0.030)	(0.031)	(0.032)	(0.034)
IO	0.526***	0.120	-0.092	-0.071	-0.079	0.050
	(0.101)	(0.108)	(0.108)	(0.109)	(0.108)	(0.105)
Log(K/L)	0.217***	0.208***	0.083***	0.089***	0.093***	0.094***
	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)
Log(Sales)	0.423***	0.367***	0.236***	0.254***	0.269***	0.245***
	(0.021)	(0.020)	(0.018)	(0.019)	(0.019)	(0.019)
Log(RDC)			0.542***	0.539***	0.532***	0.148***
			(0.020)	(0.020)	(0.020)	(0.051)
M/B				0.027***		0.023***
				(0.007)		(0.007)
Q					0.087***	
					(0.016)	
Log(P) * log(RDC)						0.116***
						(0.016)
N	58635	58635	42191	41434	41991	41434
R^2	0.398	0.407	0.551	0.554	0.553	0.559

To assess the marginal effect of stock price level on innovation (keeping all other variables constant), I use Log(P)'s estimated coefficient of 0.175 (t-value=5.47) in model (5), which suggests that future innovation is 14% higher for an average firm in the second price quartile, compared to an average firm in the lowest price quartile;[21] or 21% higher for an average firm in the highest price quartile, compared to that in the third price quartile. Thus, the effect of stock price level on firm innovation is large and economically meaningful.

To further show the channel through which stock price level affects innovation, I include Log(P)*Log(RDC), the interaction of stock price and R&D capital, in analysis. As shown in Model (6), the coefficient of the interaction is 0.116 (t-value=7.25), which is highly significant, while Log(P) becomes insignificant and its coefficient changes from 0.211 (t-value=6.81) in model (4) to 0.017 (t-value=0.50) in model (6). The coefficient of Log(RDC) also changes from 0.539 (t-value=26.95) in model (4) to 0.148 (t-value=2.90) in model (6). Taken together, the findings suggest that a large part of R&D productivity, i.e., the relation between innovation and R&D capital, is associated with stock price level, and that the channel through which high stock price level enhances innovation is to improve the R&D productivity. In other words, firms that set a higher stock price level to mitigate investor short-termism tend to have higher R&D productivity. Nevertheless, if they invest little in R&D, firms would not benefit much in innovation from setting a high stock price level.

5.2. Sensitivity Analysis

To see how sensitive the results are, I conduct the following sensitivity analyses. First, I use future citations measured at t+1, t+2, and t+3, i.e., from one year to three years

[21] This marginal effect is obtained by the coefficient estimate multiplied by the difference in the log mean price values of the two price quartiles, as shown in Panel C of Table 1.

into the future, in analysis. This is to make sure the test results are not sensitive to the way I measure future innovation at t+2. Next, in addition to the variables used by Aghion et al.'s (2013) to explain future innovation, I add to the regression model Amihud's (2002) ILLIQ (in logarithm), which measures stock illiquidity. Fang, Tian, and Tice (2013) argue that stock liquidity impedes innovation because stock liquidity encourages trading and puts pressure on managers. Third, I further extend the regression model to include firm fixed effects. This allows me to address the issues associated with possible omitted time-invariant variables.

Table 6 reports the results of the sensitivity analysis. Several things are worth mentioning. First, the regression R^2's are all around 80%, which are much higher than those around 55% reported in Table 5. Most of the increases in R^2 are due to the firm-fixed effects. This suggests that a large part of firm innovation is time-invariant. In other words, innovative (non-innovative) firms tend to remain innovative (non-innovative) for many years to come.

Second, IO is significantly negative in the t+1 regression and insignificant in the t+2 and t+3 regressions. The findings are inconsistent with Aghion et al.'s (2013) argument that institutional ownership enhances firm innovation.[22] Similarly, Log(ILLIQ) is significantly negative in the t+1 regression, insignificant in the t+2 regression, and marginally positive in the t+3 regression. The results suggest that Fang, Tian, and Tice's (2013) finding that stock liquidity impedes innovation is not robust.

[22] As noted in the footnote 20, I re-run the analyses using Aghion et al.'s (2013) posted data sample and model specifications. Aghion et al. (2013) rely on a sample of firms from 1991-1999 with innovation measures computed from the 2002 version of the patent database from NBER. They also use Poisson models as their main tests. In all these sensitivity analyses, I obtain virtually the same result, i.e., the effects of institutional ownership becomes statistically insignificant when I add to the models the log of stock price level. Furthermore, the effects from stock price level are, in all cases, statistically and economically significant.

Table 6: Share Price, IO, RDC, and Innovation

This table reports regression estimates from the following regression:

$$\log(1+CITES_{i,t+j}) = \alpha + \beta_1 IO_{i,t} + \beta_2 \log(P_{i,t}) + \beta_3 \log(RDC) + \beta_4 \log(P)*\log(RDC) + \beta_5 X_{i,t} + FirmDummy + YearDummy + e$$

where P is the Compustat PRCC_F and j denotes the number of years into the future to measure innovation (CITES). X presents a full set of log(SALES), log(K/L), M/B, and natural log of Amihud's ILLIQ. Variables definitions are in Appendix A. Sample includes non-financial US firms from 1980-2005. Firm-clustered standard errors are reported in parentheses. *, **, *** denotes statistical significance at 10%, 5%, and 1%, respectively.

	j=1	j=2	j=3
Log(P)	0.035	0.063**	0.073**
	(0.030)	(0.032)	(0.034)
IO	-0.221**	-0.003	0.048
	(0.107)	(0.112)	(0.122)
Log(K/L)	0.058*	0.052	0.039
	(0.031)	(0.033)	(0.038)
Log(Sales)	0.146***	0.160***	0.184***
	(0.033)	(0.034)	(0.037)
Log(RDC)	-0.059	-0.205***	-0.371***
	(0.043)	(0.049)	(0.060)
M/B	-0.010	-0.014**	-0.023***
	(0.007)	(0.007)	(0.007)
Log(P)*Log(RDC)	0.026**	0.037***	0.053***
	(0.010)	(0.012)	(0.016)
Log(ILLIQ)	-0.030**	-0.000	0.026*
	(0.012)	(0.013)	(0.014)
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
N	39684	37394	35187
R^2	0.828	0.812	0.797

Third, the interaction term of Log(P) and log(RDC) is significantly positive for all three regressions, consistent with the earlier finding that the productivity of R&D investments increases with the stock price level. Thus, my earlier inference that high stock price levels foster innovation is robust.

5.3. Portfolio Analysis

To illustrate how the interaction term of Log(P) and log(RDC) works, I use the portfolios of firms sorted independently by RDC and P. Specifically, each year I sort all firms into four stock price quartiles. Firms are also grouped into a zero-RDC portfolio (if they have no investment in R&D or do not report R&D in the current year and the previous 4 years) and four positive-RDC portfolios (based on RDC quartile cut-offs for firms with positive RDC). The double sorting results in 20 portfolios. Panel A of Table 7 reports the average annual patent citations for each of the 20 portfolio. Across each price level, firms with higher RDC tend to have more patent citations; and the increase of patent citations with RDC is especially strong for firms having high P. For example, for the lowest P quartile portfolios, the average annual patent citations increase from 8.1 for low-RDC firms to 294.2 for high-RDC firms, an increase of about 36 times. As for the highest P quartile portfolios, the citations increase from 13.1 for low-RDC firms to 1921.1 for high-RDC firms, an increase of about 147 times! The pattern clearly illustrates that while more R&D investments lead to more patent citations, the productivity of R&D investments is much larger for firms setting higher stock price levels.

Table 7: Citations and RDC

Each year stocks are sorted independently based on Price and RDC quartiles. Firms with no RDC are grouped separately. Panel A shows the average citations-weighted number of patents for each group while Panel B shows number of firms assigned to the group.

Panel A: Number of citations-weighted patents

	RDC=0	Low RDC	2	3	High RDC
Low Price	1.6	8.1	21.0	55.2	294.2
2	2.5	12.6	31.6	95.2	481.7
3	7.0	13.3	42.4	111.2	752.2
High Price	44.8	13.1	45.6	145.3	1,921.1
High – Low	43.2	5	24.6	90.1	1,626.9

Table 7 (cont.)

Panel B: Number of observations

	RDC=0	Low RDC	2	3	High RDC
Low Price	4466	2311	1535	732	229
2	4893	1670	1608	1184	454
3	5462	1004	1389	1738	1087
High Price	5525	486	927	1810	3681

Table 7 also reports the number of observations in each portfolio. If setting higher stock price levels is beneficial to foster innovation, we should expect that high-RDC firms would prefer to choose to keep their stock prices at higher levels. Indeed, we see that, of the 5,451 firm-year observations in the high-RDC quartile, 3,681 (67.5%) belong to the top-P quartiles and only 229 (4.2%) belong to the bottom-P quartile. Conversely, of the 5471 firm-year observations in the low-RDC quartile, only 486 (8.9%) are in the top-P quartile while 2311 (42.2%) are in the bottom-P quartile. The numbers suggest that the distributions of firm-year observations across the price quartiles for high-RDC firms and for low-RDC firms are very different. The distributions are consistent with the hypothesis that keeping high stock price levels allows innovative firms to limit speculators' influences on their price volatility and thus to mitigate investor short-termism and foster innovation.[23]

The finding of clear differences between high-RDC firms' and low-RDC firms' distribution of firm-year observations across the price quartiles leads to the conjecture that R&D investments could be an important determinant of its stock price level. To test this conjecture, I extend Dyl and Elliott's (2006) analysis to see whether RDC has any

[23] Different from firms with positive RDC, firms in the non-RDC group (RDC=0) are relatively evenly distributed across share price quartiles.

explanatory power on the variation of stock price levels beyond the proxies for investor recognition they identify.

Indeed, Table 8 shows that, in addition to EPS, firm size measured by log book equity, and log average investor holding, log RDC is also a very significant determinant of stock price level. The evidence implies that fostering innovation is a motive for high-RDC firms to keep their stock prices at high levels. In the next section, I use Probit analysis to see whether innovative firms are less likely to conduct stock splits to lower their stock price levels, which provides a robustness test on whether innovative firms indeed prefer to keep high stock price levels.

Table 8: Share Price and Firm Characteristics

This table reports the averages of the yearly cross-sectional parameter estimates from the following regressions:

$$Log(P) = \alpha + \beta_1 log(Book\ Equity) + \beta_2 log(AveHolding) + \beta_3 EPS + \beta_4 Log(RDC) + e$$

Columns (1)-(3) use sample from 1976-2001 for firms with continuous trading price data as defined in Dyl and Elliott (2006) and columns (4)-(5) use sample of US non-financial firms from 1980-2005 as defined in the current research. Variables definitions are in Appendix A. Standard errors are reported in parentheses. *, **, *** denotes statistical significance at 10%, 5%, and 1%, respectively.

	Dyl & Elliott sample			Current sample	
	(1)	(2)	(3)	(4)	(5)
EPS		0.095***	0.081***	0.114***	0.122***
		(0.007)	(0.007)	(0.007)	(0.005)
Log(Book Equity)		0.168***	0.135***	0.214***	0.199***
		(0.009)	(0.012)	(0.008)	(0.005)
Log(AveHolding)		0.157***	0.204***	0.050***	0.068***
		(0.013)	(0.020)	(0.006)	(0.008)
Log(RDC)	0.209***		0.049***		0.026***
	(0.006)		(0.007)		(0.005)
Intercept	2.450***	1.418***	1.346***	1.520***	1.475***
	(0.039)	(0.030)	(0.052)	(0.028)	(0.028)
Number of years	25	26	25	24	24
Average R^2	0.40	0.61	0.69	0.55	0.58
Average ob. Per year	330	755	320	2688	1830

CHAPTER 6: REVERSE CAUSALITY

As I mentioned in the Introduction, it is possible that investors may bid up a firm's stock price when they anticipate more future innovation by the firm. In this case, it is innovation causing high stock price, rather than high stock price enhancing innovation. But, the firm can decide to keep its high stock price level or to split its shares to lower its stock price level. In fact, many firms split their stocks to manage their stock price levels (Weld et al 2009, Dyl and Elliott 2006, among others). Thus, I conduct two additional robustness tests. The first one is on a sample of stock splits in which managers re-set the stock price levels, and the second test on a sample of IPOs in which the offering price range is also set by managers. Thus, these two robustness checks would allow me to see whether managers of innovative firms actively set their stock price levels to mitigate investor short-termism and foster innovation.

6.1. Stock Splits and Firm Innovation

If it is more innovation causing higher stock price, innovation should not change following stock splits. Conversely, if it is higher stock price that fosters innovation, we expect innovation to decline following stock splits, because stock splits automatically lower stock price levels and lead to more speculative trading by retail investors, as Brandt et al. (2010) show. Since my hypothesis emphasizes that innovative firms would keep their stock prices at higher levels to guard against investor short-termism, stock splits would weaken this function.

Asquith, Healy, and Palepu (1989) observe that split firms tend to experience considerable earnings growth prior to stock splits, and argue that stock splits are used to

convey that the recent earnings growth is permanent. McNichols and Dravid (1990) further show that firms conduct splits to signal improvements in earnings. It is possible that split firms no longer need to keep high stock price levels to guard against investor short-termism; instead, it could enhance their firm values by using stock splits to attract more speculative traders to look at their improvements in earnings. This reasoning is in line with my hypothesis, and suggests that firms actively manage their stock price levels according to their needs—i.e., when they invest more in R&D and pursue innovation, they tend to keep high stock price levels; conversely, they use stock splits to lower their stock price levels when they want to emphasize their earnings. Thus, based on my hypothesis, I predict that (i) innovative firms are less likely to engage in stock splits, and (ii) if they do, innovation would decline following stock splits.

To test these predictions, I analyze a sample of 6,088 firms that split their stocks. I identify this sample by first collecting firms in the CRSP database that split their shares (CRSP distribution code DISTCD = 5523 or 5533) during the sample period. Each stock split event is then matched with the annual innovation data. For firms that have multiple splits in a year, I aggregate the split factors (FACSHR) to get a cumulative split factor for the whole year. To focus on stock splits that have large effects on stock price levels, I exclude firms with the yearly cumulative split factor of less than 0.25 from the sample. I use the split factor to measure the relative change in stock price levels induced by stock splits. Since more than half of the splitting firms do not have any patent citations around the split year, Table 9 reports summary statistics for the whole split sample and for the subsample of split firms with positive patent citations. The table report statistics before firms conduct splits as well as for the changes of the key variables following stock splits.

Table 9: Descriptive Statistics for Splitting Firms

This table report summary statistics for a sample of firms that split stocks. The whole split sample includes domestic, non-financial firms from the 1980-2005 period that split shares with split factors from 0.25 to 3.5; and the Innovative split sample is the whole split sample excluding firms with no patent citations the year before and after stock splits Variable definitions are in Appendix A.

	Whole	Split	Sample	Innovative	Split	sample
Variable	Obs	Mean	S.D.	Obs	Mean	S.D.
FACSHR	6088	0.816	0.459	1775	0.879	0.454
$\text{Log(1+CITES)}_{t-1}$	5420	1.544	2.439			
IOR_{t-1}	5420	0.363	0.246			
Log(SALES)_{t-1}	5420	5.414	1.869			
Log(M/B)_{t-1}	5390	1.035	0.763			
Return12_{t-1}	5002	0.705	1.106			
Log(P)_{t-1}	5420	3.314	0.664			
$\text{Sales growth}_{t-1}$	4461	0.206	0.262			
$\Delta\text{log(1+Cites)}_{t+2, t-1}$	6088	-0.017	1.300	1775	-0.057	2.088
$\Delta\ \text{IO}_{t, t-1}$	5420	0.041	0.107	1775	0.024	0.092
$\Delta\ \text{Log(K/L)}_{t, t-1}$	5420	0.088	0.262	1775	0.071	0.167
$\Delta\ \text{Log(Sales)}_{t, t-1}$	5420	0.296	0.337	1775	0.220	0.269
$\Delta\ \text{Log(RDC)}_{t, t-1}$	3968	0.077	0.205	1775	0.128	0.243

Table 9 reports that, on average, innovation declines slightly following stock splits. However, there is a significant increase in institutional ownership. IO increases by 4.1% and 2.4% from the beginning value to the ending value of the split year in the whole split sample and innovative split sample, respectively.

To further examine the characteristics of firms that split shares, I run a probit regression to see what firm characteristics may affect the split decision. Specifically, I estimate the following regression:

$$\text{Prob(SPLIT=1)}_t = \Phi(\beta_0 + \beta_1\text{Log(Innovation)}_{t-1} + \beta_2\text{IO}_{t-1} + \beta_3 X + \text{Industry\_DM} + \text{Year\_DM} + \varepsilon_t) \quad (3)$$

where, as before, $\Phi(\cdot)$ is a cumulative Gaussian distribution function, subscript t indicates the year during which firm split their shares, SPLIT is a dummy variable that takes the value of 1 for splitting firms and 0 otherwise, Innovation is either RDC or CITES, and X is a matrix of factors that potentially affect split decisions. The matrix X includes Sales, M/B, cumulative returns in the last 12 months, Price level, and Sales growth, as suggested by Chemmanur, Hu, and Huang (2014). I provide the definition of these variables in Appendix A.

Panel A of Table 10 reports the probit regression results. The results show that the coefficients on both log(RDC) and log(1+CITES) are significantly negative in all settings, implying that innovative firms are less likely to split their share. The coefficient on IO is also negative, suggesting that firms with high IO are also less likely to do stock splits. The evidence is consistent with Dyl and Elliott (2006), who show that firms that can attract more institutional investors tend to keep higher stock price levels. This finding, along with the increase in institutional ownership after stock split presented in Table 9, suggests that some institutional investors are attracted by splitting firms and increase their holdings in these firms. Also, the results from Table 10 are consistent with Lakonishok and Lev (1987) and McNichols and Dravid (1990) that firms having higher stock prices, higher past stock returns, higher M/B ratio, and higher sales growth, are more likely to split their shares.

To access the changes of innovation output in the years subsequent to stock splits, I estimate the following regression:

$$\Delta \log(1+\text{Cites})_{t+2,\, t-1} = \beta_0 + \beta_1 \text{FACSHR} + \beta_2 \Delta \text{IO}_{t,\, t-1} + \beta_3 \Delta \log(\text{K/L})_{t,\, t-1} + \beta_4 \Delta \text{size}_{t,\, t-1} + \beta_5 \Delta \log(\text{RDC})_{t,t-1} + \text{Industry FE} + \text{Time FE} \quad (4)$$

where the dependent variable is the change in innovation output 2 years after split compared to before split and the independent variables include the split factor, changes in IO, K/L, firm

size, and R&D stock before and after the splits. The sample is restricted to firms that split their shares with annual FACSHR greater than or equal to 0.25. I conduct the test on the whole split sample that includes all splitting firms and on the subsample that only includes split firms with positive patent citations the year before or after split.

Table 10: Stock Split and Innovation

Panel A: Stock Split Determinants

This table present Probit regressions of stock split dummy on other independent variables measured at the beginning of the year of the stock split:

$$Prob(SPLIT=1)_t = \Phi(\beta_0 + \beta_1 Log(Innovation)_{t-1} + \beta_2 IO_{t-1} + \beta_3 X + Industry\_DM + Year\_DM + \varepsilon_t)$$

where Innovation is either RDC or CITES. Variables definitions are in Appendix A. Industries are Compustat 3-digit SIC codes. Sample includes firms in the intersection of splitting firms with annual cumulative split factor of at least 0.25 and the main sample specified in Table 1. Sample is from 1980 to 2005 (citations measured up to 2006). Robust firm cluster standard errors are reported in parentheses; *, **, *** denotes statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
$Log(RDC)_{t-1}$		-0.048***	-0.025***		
		(0.006)	(0.010)		
$Log(1+CITES)_{t-1}$				-0.033***	-0.016***
				(0.005)	(0.006)
IO_{t-1}	-0.287***	-0.242***	-0.365***	-0.265***	-0.368***
	(0.068)	(0.077)	(0.082)	(0.068)	(0.073)
$Log(SALES)_{t-1}$	-0.095***	-0.087***	-0.141***	-0.084***	-0.135***
	(0.009)	(0.010)	(0.013)	(0.009)	(0.011)
$Log(M/B)_{t-1}$	0.123***	0.167***	0.122***	0.138***	0.105***
	(0.018)	(0.021)	(0.025)	(0.018)	(0.021)
$Return12_{t-1}$	0.278***	0.306***	0.253***	0.272***	0.224***
	(0.022)	(0.025)	(0.025)	(0.022)	(0.022)
$Log(P)_{t-1}$	0.736***	0.735***	0.944***	0.753***	0.944***
	(0.039)	(0.046)	(0.050)	(0.041)	(0.045)
Sales growth $_{t-1}$	0.165***	0.264***	0.239***	0.158***	0.132***
	(0.027)	(0.040)	(0.041)	(0.028)	(0.030)
Industry Dummies	No	No	Yes	No	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
N	36820	29806	29508	36820	36623
R^2	16.11	16.18	19.36	16.37	19.41

Table 10 (cont.)

Panel B: Stock Split and Change in Innovations
This table reports regression coefficients of changes in future cite-weighted patents on firm characteristics and stock split factor:

$$\Delta \log(1+Cites)_{t+2,\,t-1} = \beta_0 + \beta_1 FACSHR + \beta_2\, \Delta\, IO_{t,\,t-1} + \beta_3\, \Delta \log(K/L)_{t,\,t-1} + \beta_4\, \Delta\, size_{t,\,t-1} + \beta_5\, \Delta \log(RDC)_{t,t-1} + \text{Industry FE} + \text{Time FE}$$

Dependent variable is the change in Innovations two years after splits and before stock splits, measured as $\log(1+Cites)_{t+2} - \log(1+Cites)_{t-1}$. Independent variables include change from before and after splits in institutional ownership (Δ IO), change in capital labor ratio (Δ log(K/L)), change in firm sale (Δ Size), and change in R&D stock (Δ RDC), and Split factor (FACSHR from CRSP). The split factor is set to 0 in years with no stock splits. Whole split sample for regressions in the columns (1)-(3) includes domestic, non-financial firms from 1980-2003 that split shares with split factors from 0.25 to 3; and Innovative sample for the last two columns (4)-(5) is the whole split sample excluding firms with no patent citations the year before and after stock splits. Industries are defined as Compustat 3-digit SIC codes. Robust standard errors are reported in parentheses; *, **, *** denotes statistical significance at 10%, 5%, and 1%, respectively.

Sample	Whole split sample			Innovative split sample	
	(1)	(2)	(3)	(4)	(5)
Δ IO	0.453*	0.406	0.351	0.476	0.248
	(0.247)	(0.247)	(0.261)	(0.532)	(0.575)
Δ log(K/L)	-0.017	-0.015	0.001	-0.117	-0.010
	(0.088)	(0.088)	(0.095)	(0.376)	(0.403)
Δ Size	-0.022	0.002	-0.009	0.208	0.245
	(0.101)	(0.100)	(0.106)	(0.208)	(0.218)
Δ log(RDC)	0.081	0.095	0.108	0.168	0.089
	(0.141)	(0.142)	(0.159)	(0.234)	(0.255)
Split factor		-0.135***	-0.139**	-0.217**	-0.252**
		(0.050)	(0.055)	(0.101)	(0.114)
Industry FE	No	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	3968	3968	3968	1775	1775
R^2	0.054	0.056	0.102	0.152	0.246

Regression results, reported in Panel B of Table 10, show that, among splitting firms, innovation declines more for firms that choose a larger split factor (the coefficient on FACSHR is significantly negative) while IO virtually has no effect.[24] The evidence is thus

[24] Since changes in innovation around stock splits might be irrelevant for non-innovative firms (i.e. firms without any patent citations), model (3) works better in the sample of innovative splitting firms (columns 4 and

consistent with my hypothesis that higher P enhances innovation, but inconsistent with the notion that the positive association between innovation and P is due to more innovation causing higher stock price.

6.2. IPO Offering Price and Firm Innovation

I do the second robustness test on the association between stock price level and innovation by focusing on a sample of IPO firms identified from the Thomson Financial SDC New Issues database. I use the mid-point of the lowest and highest initial filing price as the IPO price. The filing price range is of the managers' choice and is not affected by the feedback from the financial markets after firms announce their IPOs. In addition, I also repeat my tests with the actual IPO offering price. After merging the IPO data with my main sample (including firms with PRCC_F of less than $5 since I are relying on IPO price), I am left with 4,716 IPO firms with valid data on IPO offering Prices. Finally, the subsample consisting of firms with valid IPO filing prices has 3550 observations. Table 11 reports summary statistics of the key variables for the IPO sample.

On average, institutional investors own 19% (median 15%) shares of IPO firms, consistent with previous studies (see, e.g., Fernando, Krishnamurthy, and Spindt (2004)). Similarly, the average filing price is $10.6 and the average offering price is $11.8. Also, more than half of IPO firms in the sample did not report R&D expenditures when they went for IPO.[25]

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5) which yields higher R2 values. Also, the magnitude of the split factor coefficient estimates is larger in this sample.

[25] I use R&D of the IPO year instead of R&D capital from previous 5 years due to data limitation on IPO firms

Table 11: IPO Sample Characteristics

This table reports descriptive statistics of a sample of IPO firms. Offer Price is the IPO offering price; Middle Price is the average of the low and high IPO filing prices; R&D is R&D expenditure. Other variables are described in Table 1. Sample includes IPO firms from SDC New Offering database that are merged with domestic, non-financial firms from CRSP/Compustat intersection database from 1980 – 2003. Firms with missing values of IOR, K/L, Sales, or Offering Price are excluded.

Variables	n	Mean	S.D.	Median
CITES	4716	35.47	437.7	0
Offer Price	4716	11.08	5.44	11
Mid-point Filing Price	3550	10.58	4.93	11
IO	4716	0.19	0.18	0.15
Log(K/L)	4716	3.34	1.2	3.26
Log(Sales)	4716	3.3	2	3.53
Log(1+R&D)	4716	0.73	1.02	0

Table 12: IPO Price and Innovation

This table reports OLS regression estimates of future innovation on IPO firms' characteristics:

$$\log(1+CITES_{i,t+2}) = \alpha + \beta_1 IO_{i,t} + \beta_2 \log(P_{i,t}) + \beta_3 X_{i,t} + Industry + Year + e$$

where P is either IPO mid-point filing price or IPO actual offering price. Variables definitions are in Appendix A. Year and industry dummies are included in all regressions. Firm cluster standard errors are reported in parentheses. *, **, *** denotes statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
IO	0.406**		0.231		0.259
	(0.183)		(0.227)		(0.187)
Log(Filing Price)		0.268***	0.246***		
		(0.078)	(0.081)		
Log(Offer Price)				0.280***	0.257***
				(0.066)	(0.068)
Log(K/L)	0.079***	0.064**	0.062**	0.069***	0.067***
	(0.023)	(0.028)	(0.028)	(0.023)	(0.023)
Log(Sales)	-0.019	-0.068***	-0.073***	-0.050**	-0.056***
	(0.018)	(0.024)	(0.025)	(0.021)	(0.022)
Log(1+R&D)	0.757***	0.865***	0.864***	0.738***	0.737***
	(0.046)	(0.062)	(0.063)	(0.046)	(0.046)
N	3702	2812	2812	3702	3702
R^2	0.364	0.385	0.385	0.366	0.367

Table 12 reports regression model (1) for IPO firms on IPO filing price. It shows that firms that set a higher midpoint of IPO offering price range tend to have more future innovation. The results are almost the same when I use the final IPO offering price as P. Since future innovation is significantly related to the midpoint of the offering price range or the final offering price, the evidence is again consistent with the hypothesis that innovative firms set high stock price levels to mitigate short-termism and enhance innovation.

CHAPTER 7: CONCLUSION

This essay compares the roles of institutional ownership and stock price levels in the governance of firm innovation. Based on the notion that, by keeping high stock price levels, firms can reduce speculative trading by retail investors and reduce price volatility, I hypothesize that high prices allow firms to mitigate short-termism and enhance innovation.

Indeed, I find that high-priced firms are less likely to cut R&D to reverse poor earnings performance, and that, unlike Bushee's (1998) finding, IO shows no effect on the R&D policy in the presence of P. I also find that, unlike Aghion et al.'s (2013) finding, IO has no effect on CEO firing and on firm innovation in the presence of P; rather, it is high-priced firms that are less likely to oust their CEOs and are more innovative. These findings cast doubt on the claim that institutional investors play a positive role in the governance of innovation because of their monitoring and long-term views. Instead, the functions of IO found in the extant literature in the governance of innovation are largely derived from IO's correlation with P.

I further use two robustness checks to verify my findings. In the first check, I discover that firm innovation declines after stock splits. In the second check, I reveal that IPO firms with a higher offering price range are more innovative. The results in these two cases suggest that managers of innovative firms actively support high stock price levels to facilitate innovation, rather than being "forced" or "assured" by institutional investors in order to pursue innovation.

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APPENDIX A: VARIABLES DEFINITION

All variables, unless otherwise noted, are calculated at fiscal yearend, denoted as year t. Missing values for Institutional ownership IO, R&D expenditures XRD, or CITES are set to zero.

Variable	Definition	Data Source
Common variables		
Innovation (CITES)	Number of truncation-adjusted patents (that are granted) weighted by future citations measured at patent application year. $CITES_{i,t} = \sum_{j \in i} (ALLCITES * HJTWT)_{j,t}$	NBER 2006
COUNTS	Number of patents (that are granted) measured at patent application year	NBER 2006
Price level (P)	PRCC_F, or	Compustat
	Average trading price during the previous 12 months	CRSP monthly
Institutional Ownership (IO)	IO, aggregate share holding of all institutions scaled by total shares outstanding at the end of the quarter closest to fiscal yearend month	Spectrum 13f
Capital-Labor (K/L)	PPENT/EMP	Compustat
Firm size (SALES)	SALES	Compustat
R&D Stock (RDC)	$R\&D_t + 0.8*R\&D_{t-1} + 0.6*R\&D_{t-2} + 0.4*R\&D_{t-3} + 0.2 * R\&D_{t-4}$	Compustat
Market-to-Book (M/B)	ME/BE where	Compustat
	ME = CSHO * PRCC_F	
	BE = Stock Equity (SEQ, CEQ+PSTK, AT-LT, or 0 depending on availability) + Deferred Taxes (TXDITC) - Preferred Equity (PSTKRV, PSTKL, PSTK, or 0 depending on availability)	
Tobin's Q	(ME + AT - CEQ - TXDB) / AT	Compustat
Illiquidity (ILLIQ)	Amihud's ILLIQ, the average over year	CRSP

Variable	Definition	Data Source
	of 1000000*abs(Return) / (abs(Price)*Volume)	
<u>IO Determinants</u>		
9-month Stock Return (R9)	Cumulative monthly stock return from month -12 to month -3 relative to fiscal year ending month.	CRSP
3-month Stock Return (R3)	Cumulative monthly stock return from month -3 to month 0 relative to fiscal year ending month.	CRSP
Dividends (DIV)	DVC / ME	Compustat
Firm Age (AGE)	Number of years the firm has valid stock price on CRSP	CRSP
Turnover (TO)	annual average of monthly share turnover	CRSP
Volatility (VOL)	standard deviation of monthly stock returns over last two years	CRSP
S&P500 membership (SP500)	1 if SPMIM=10, 0 otherwise	Compustat
Capital Expenditure (CAPX)	CAPX / AT	Compustat
R&D expense (RDAT)	XRD / AT	Compustat
Tangibility (TANG)	PPENT / AT	Compustat
<u>R&D cut determinants</u>		
Indicator for R&D cut (CUTRD)	1 if $(XRD_t - XRD_{t-1}) < 0$, 0 otherwise	Compustat
Prior change in R&D (PCRD)	$\ln(XRD_{t-1}) - \ln(XRD_{t-2})$	
Change in industry R&D (CIRD)	$\ln(IRD_t / ISALES_t) - \ln(IRD_{t-1} / ISALES_{t-1})$	
Change in Capital Expenditure (CCAPX)	$\ln(CAPX_t) - \ln(CAPX_{t-1})$	
Change in Sales (CSALES)	$\ln(SALES_t) - \ln(SALES_{t-1})$	

Variable	Definition	Data Source
Distance from earnings goal (DIST)	$(EARNING_t+XRD_t)-(EARNING_{t-1}+XRD_{t-1})) / XRD_{t-1}$ where	
	EARNING = IBCOM + TXDI + ITCI + TIE	
FCF before R&D (FCF)	$(OIBDP_t + XRD_t) / AT_{t-1}$	
CEO turnover variables		Aghion et al.
CEO Exit	1 if forced CEO exit, 0 otherwise	
Share Price determinants		
Average Holding (AveHolding)	BE / CSHR	Compustat
Earnings per Share (EPS)	EPS	Compustat
Stock Split determinants		
Split dummy	1 if a firm splits share during the year with split factor of at least 0.25,	CRSP
	0 otherwise	
Split factor (FACSHR)	Π(1+FACSHR)-1 for each fiscal year	CRSP
Change in Institutional Ownership (Δ IO)	$IO_t - IO_{t-1}$	Spectrum 13f
Change in capital labor ratio (Δ log(K/L)	$\ln(K/L_t) - \ln(K/L_{t-1})$	Compustat
Change in firm sale (Δ Size)	$\ln(SALES_t) - \ln(SALES_{t-1})$	Compustat
Change in R&D stock (Δ RDC)	$\ln(RDC_t) - \ln(RDC_{t-1})$	Compustat
IPO variables		
Offering Price (P_OFFER)	Official IPO offering price	SDC
Filing Price (P_FILE)	MFILE: Mid-point of the price range (high and low) in IPO initial filing at which firms expect to offer their shares	SDC

APPENDIX B: ROBUSTNESS TESTS ON AGHION, VAN REENEN, AND ZINGALES'S (2013) SAMPLE

Aghion, Van Reenen, and Zingales (AVZ, 2013) report significant positive effects of institutional ownership on firm innovation. They make available online their complete datasets and programming codes used to generate their empirical results. Their main sample includes firm-year observations from 1991-1999. The citations-weighted patents are calculated based on NBER patent database updated to 2002.I utilize these datasets and codes to robustly test the hypothesis that it is high price levels set by managers, rather than institutional investors, that foster firm innovation.

First, I reproduce regressions tables reported in their paper. I then merge this sample with a sample of US firms (fic=”USA”) with non-missing trading price level PRCC_F taken from Compustat. In the merged dataset, I lost around 2.5% of the total observations due to missing price. Alternatively, I merge the AVZ sample with average trading prices in the previous 12 months obtained from CRSP for firms with share codes of 10 or 11. I repeat all the tests in AVZ with an added independent variables log(Price). I report these robustness tests in Tables B1 through B3 with Price taken from Compustat PRCC_F. The results with average price from CRSP are qualitatively the same and so skipped.

1. Main empirical results (AVZ Table 1)

Table B1 replicates Table 1 in AVZ (2013), column by column, and shows that in all regressions P has significant and positive effect on innovation. The magnitude of the effect of P is qualitatively the same compared to the estimates from my own sample reported in Table 5. In contrast, the effects of IO disappears in the presence of P in 7 out of 8 models. IO is marginally significant in model (8) with Negative Binomial regression. The evidence from this Table supports my hypothesis.

2. Testing the implications of the Career Concerns Hypothesis with the Lazy Manager Hypothesis (AVZ Table 2)

AVZ (2013) contrast the Career Concerns Hypothesis with the Lazy Manager Hypothesis and provide tests that support the Career concerns hypothesis. Specifically, the two hypotheses would bring different consequences in different firm settings. First, with different product market competition levels the two hypotheses predict differently the effect of IO on innovation: The Career Concern Hypothesis predicts a complement effect of product market competition and IO on innovation while the Lazy Manager Hypothesis predict the two a substitution effect. AVZ provide evidence that IO has stronger effect on innovation in more competitive markets,

consistent with the prediction of the Career Concern Hypothesis. I add share price as a potential governance factor into their original regression models and report results in Table B2.

Table B2 shows that even in more competitive industries, IO loses its effect on innovation in the presence of P.

The next test that I rerun is the test on CEO turnover. I present this test in the main body of this paper. Overall, in the presence of P, IO does not show its effect of reducing the likelihood of CEO firings in the face of profit downturns.

3. Selection issues (AVZ Table 5)

AVZ discuss in details the selection issues. The reasons is that institutional investors may select firms with high innovation to invest in, rather than providing incentives for managers to invest in innovation. One of the tools they use to tackle the selection issue is utilizing the inclusion to the S&P500 index as an instrumental variable for IO. The addition to the index is likely to attract more IO but is unlikely to directly affect firm innovation. After dealing with endogeneity with instrumental variables, the effects from IO on innovation reported by AVZ 2013 remain significant with a much larger magnitude.

I repeat these tests and report updated results in Table B3. The results from Table B3 shows that even though instrumental variable helps IO avoid being biased downward, the inclusion of P into the regressions still takes away all the effects on IO.

Table B1: Institutional Ownership and Innovation (AVZ Table 1)

This table reproduces AVZ Table 1 (columns "Original") along with share price P as an additional control variable (columns "New"). P is share price, PRCC_F, taken from Compustat for US firms.
AVZ Caption: Firms in all columns: 803. *CITES* is a count of a firm's patents weighted by the number of future citations. Coefficients above standard errors clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies and time dummies. Estimation period is 1991–1999 (citations up to 2002); fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator.

AVZ column	1		2		3		4	
Model	OLS		OLS		Poisson		Poisson	
Dependent variable	Ln(Cites)		Ln(Cites)		Cites		Cites	
	Original	New	Original	New	Original	New	Original	New
IO	0.006***	0.002	0.005***	0.001	0.010***	0	0.008***	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Log(P)		0.216***		0.206***		0.217***		0.274***
		(0.062)		(0.056)		(0.077)		(0.073)
Log(Sales)	0.568***	0.523***	0.310***	0.269***	0.820***	0.781***	0.349***	0.305**
	(0.037)	(0.042)	(0.045)	(0.048)	(0.042)	(0.043)	(0.117)	(0.125)
Log(K/L)	0.433***	0.473***	0.261***	0.309***	0.483***	0.537***	0.346**	0.396**
	(0.094)	(0.096)	(0.085)	(0.085)	(0.136)	(0.146)	(0.165)	(0.181)
Log(RDC)			0.337***	0.340***			0.493***	0.477***
			(0.04)	(0.04)			(0.14)	(0.138)
FE	No	No	No	No	No	No	No	No
Observations	4025	3903	4025	3903	6208	6034	6208	6034

(Table B1 cont.)

AVZ column	5		6		7		8	
Model	Poisson		Negative Binomial		Negative Binomial		Negative Binomial	
Dependent variable	Cites		Cites		Cites		Cites	
	Original	New	Original	New	Original	New	Original	New
IO	0.007***	-0.002	0.009***	0.004*	0.008***	0.003	0.006***	0.003*
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(Sales)	0.184***	0.187***	0.493***	0.399***	0.229***	0.154**	0.127***	0.080**
	(0.063)	(0.066)	(0.047)	(0.058)	(0.058)	(0.066)	(0.037)	(0.041)
Log(K/L)	0.440***	0.507***	0.613***	0.632***	0.343***	0.385***	0.264***	0.301***
	(0.132)	(0.137)	(0.106)	(0.103)	(0.087)	(0.085)	(0.076)	(0.076)
Log(P)		0.158***		0.419***		0.337***		0.161***
		(0.051)		(0.07)		(0.061)		(0.049)
Log(RDC)	0.009	-0.003			0.448***	0.450***	0.178***	0.185***
	(0.107)	(0.102)			(0.039)	(0.039)	(0.029)	(0.03)
FE	Yes	Yes	No	No	No	No	Yes	Yes
Observations	6208	6034	6208	6034	6208	6034	6208	6034

Table B2**:** Product Market Competition, IO, and Innovation (AVZ Table 2)

This table reproduces AVZ Table 2 (columns "Original") along with share price P as an additional control variable (columns "New"). P is share price, PRCC_F, taken from Compustat for US firms.
AVZ Caption: The dependent variable is future cite-weighted patents. Each column is a separate Poisson regression, as in AVZ Table 1, column 5. All regressions control for year dummies, ln(sales), ln(capital/labor), ln(R&D stock), four-digit industry dummies, and fixed effects using Blundell, Griffith, and Van Reenen (1999) method. Standard errors are clustered at the three-digit industry level. Product market competition constructed as (1 − Lerner index) where Lerner is calculated as the median gross margin from the entire Compustat database in the firm's three-digit industry. Estimation period is 1991–1999 over 803 firms. High (low) market power industries are those where (1 −Lerner) is above (below) the sample median (0.871 for columns 3 and 4 and 0.877 in columns 7 and 8).

AVZ column	(1)		(2)		(5)		(6)	
Measure of competition	Varies over time		Varies over time		Constant over time		Constant over time	
Sample	Pooled		Pooled		Pooled		Pooled	
	Original	New	Original	New	Original	New	Original	New
Log(P)		0.158***		0.159***		0.158***		0.159***
		(0.055)		(0.053)		(0.055)		(0.053)
IO	0.007***	-0.002	-0.064**	0.007	0.007***	-0.002	-0.068**	0.004
	(0.002)	(0.001)	(0.030)	(0.023)	(0.002)	(0.001)	(0.028)	(0.022)
1 – Lerner	0.343	-0.218	-3.694	0.277				
	(2.329)	(2.274)	(3.330)	(2.803)				
IO * (1 – Lerner)			0.082**	-0.010			0.087***	-0.007
			(0.035)	(0.026)			(0.033)	(0.025)
Observations	6208	6034	6208	6034	3123	3037	6208	6034

Table B2 (Cont.)

AVZ column	(3)		(4)		(7)		(8)	
Measure of competition	Varies over time		Varies over time		Constant over time		Constant over time	
Sample	High Competition		Low Competition		High Competition		Low Competition	
	Original	New	Original	New	Original	New	Original	New
Log(P)		0.166***		0.191		0.159***		0.234
		(0.032)		(0.127)		(0.035)		(0.146)
IO	0.009***	-0.001	0.002	-0.004	0.009***	-0.001	0	-0.002
	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.003)	(0.004)
1 – Lerner	4.668**	5.492**	1.376	1.049				
	(2.31)	(2.285)	(4.947)	(4.349)				
Observations	3085	2997	3123	3037	3125	3039	3083	2995

Table B3: Instrumental Variables (AVZ Table 5)

This table reproduces AVZ Table 5 (columns "Original") along with share price P as an additional control variable (columns "New"). P is share price, PRCC_F, taken from Compustat for US firms.
AVZ Caption: All columns control for ln(sales), ln(capital/employment), four-digit industry dummies, and time dummies. Columns 7–10 also include the time-varying Lerner index. Estimation period is 1991–1999. S&P 500 is a dummy variable equal to unity if the firm is a member of the S&P 500 Index. FE (Fixed effects) controls use the Blundell, Griffith, and Van Reenen (1999) method. Exogeneity test is a Hausman-based test. 803 firms in full sample. "High (Low) Comp." is the subsample where the industry (1−Lerner) is above (below) the sample median (0.871), as in Table 2. Standard errors are clustered at the firm level on columns 1–6 and at the three-digit industry level (as we are using competition information at this level) in columns 7–8.

AVZ column	(1)		2	3		4	
			1st stage	2nd stage	2nd stage		
Dep. variable	cites	cites	IO	cites	cites	cites	cites
	Original	New	Original	Original	New	Original	New
IO	0.010***	0.000		0.043***	0.054	0.007***	-0.002
	(0.002)	(0.003)		(0.012)	(0.046)	(0.002)	(0.003)
Log(P)		0.217***			0.227***		0.160***
		(0.077)			(0.078)		(0.048)
z_sp500			9.238***				
			(2.284)				
FE	No	No	No	No	No	No	No
N	6208	6034	6208	6208	6034	6208	6034

Table B3 (Cont.)

AVZ column	5	6		7 High Comp Sample		8 Low Comp. Sample	
	1st stage	2nd stage					
Dep. variable	IO Original	cites Original	cites New	cites Original	New	cites Original	New
IO		0.029**	-0.020	0.041***	0.141***	0.016	0.022
		(0.013)	(0.043)	(0.006)	(0.032)	(0.019)	(0.031)
Log(P)			0.155***		0.169***		0.209
			(0.050)		(0.044)		(0.156)
z_sp500	8.872***						
	(2.352)						
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6208	6208	6034	3085	2997	3123	3037

VITA

Huong Le was born in Ninh Binh, Vietnam. She earned her Bachelor of Science in International Economics in 2001 and Master of Arts in Economics in 2005 from Foreign Trade University, Vietnam. She became a lecturer of E-commerce at Foreign Trade University in 2006. She started the doctoral program in Finance at Louisiana State University in August 2009, and will earn her Doctor of Philosophy degree in May 2015.