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Essays on corporate innovation

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TABLE OF CONTENTS

LIST OF TABLES

LISTS OF FIGURES

ABSTRACT

In this dissertation, I explore the underlying mechanisms through which a firm innovates and invests in Research and Development (R&D). It consists of two essays.

The initial essay investigates the effects of aggregate stock market liquidity on innovation at both the aggregate and firm levels for publicly traded firms in the U.S., and shows a significant and positive effect at both levels of aggregation. Next, the essay provides two underlying mechanisms through which aggregate stock liquidity enhances innovation. First, high stock market liquidity reduces the cost of raising external capital, making it easier for firms, especially for small firms and those with R&D investments, to issue equity and finance their innovations. Second, high stock market liquidity generates high firm valuation and reduces transaction costs, motivating large firms to buy the innovations of small firms through merger and acquisition activities. Overall, this essay documents that aggregate stock market liquidity plays a very important and positive role in enhancing aggregate innovation.

The second essay examines how a firm makes investment decisions under uncertainty. Real option theory predicts an inverse relationship between corporate investment and uncertainty, because investment is (at least partially) irreversible and uncertainty increases the value of the option to wait. In contrast, the strategic growth option framework shows that uncertainty may encourage investment in growth options since the value of the option to wait is drastically eroded due to competition and an initial investment can confer greater capacity to take advantage of future growth opportunities. Consistent with the strategic growth option analysis, this essay documents that firms will invest more in R&D when facing high uncertainty. The reason is that R&D investments

can potentially generate growth opportunities which enhance competitive advantages for firms in the future. The study further shows that the switch of more R&D investments and less capital expenditures is more pronounced for firms with fewer real options, i.e., firms that are large, less innovative, or firms in more competitive industries. Finally, this essay documents that these strategic advantages are important factors to derive the investment policies of firms operating in an uncertain environment.

CHAPTER 1: STOCK MARKET LIQUIDITY AND INNOVATION ACTIVITY

1.1 Introduction

A wide literature documents the important role of financial markets in enhancing firm innovation and the contribution of innovation to economic growth (e.g. Hall et al. (2011)). However, locating the channels through which these markets effect innovation, a major driver of economic growth, has been controversial (Brown et al. (2009)). In this paper, I investigate the effects of stock market liquidity on innovation at both the aggregate and firm levels for publicly traded firms in the U.S. This topic is important to market participants including regulators because stock market liquidity can be altered by changes in investor behaviors, firm decisions and/or financial market regulations; such as the change in disclosure requirements, deregulation of stock commission or reduction of tick size.

As a preliminary inquiry, Figure 1 plots the aggregate U.S. stock liquidity based on Amihud’s (2002) illiquidity measure and the aggregate number of patent applications by publicly traded firms on the CRSP database from 1975 through 2006. The figure shows that the U.S. stock markets have become more liquid and that the number of patent applications has increased gradually through 2002, when the tech bubble burst, and beyond. These patterns suggest a positive relationship between aggregate stock market liquidity and aggregate innovation for all publicly traded firms in the U.S during this period of time.

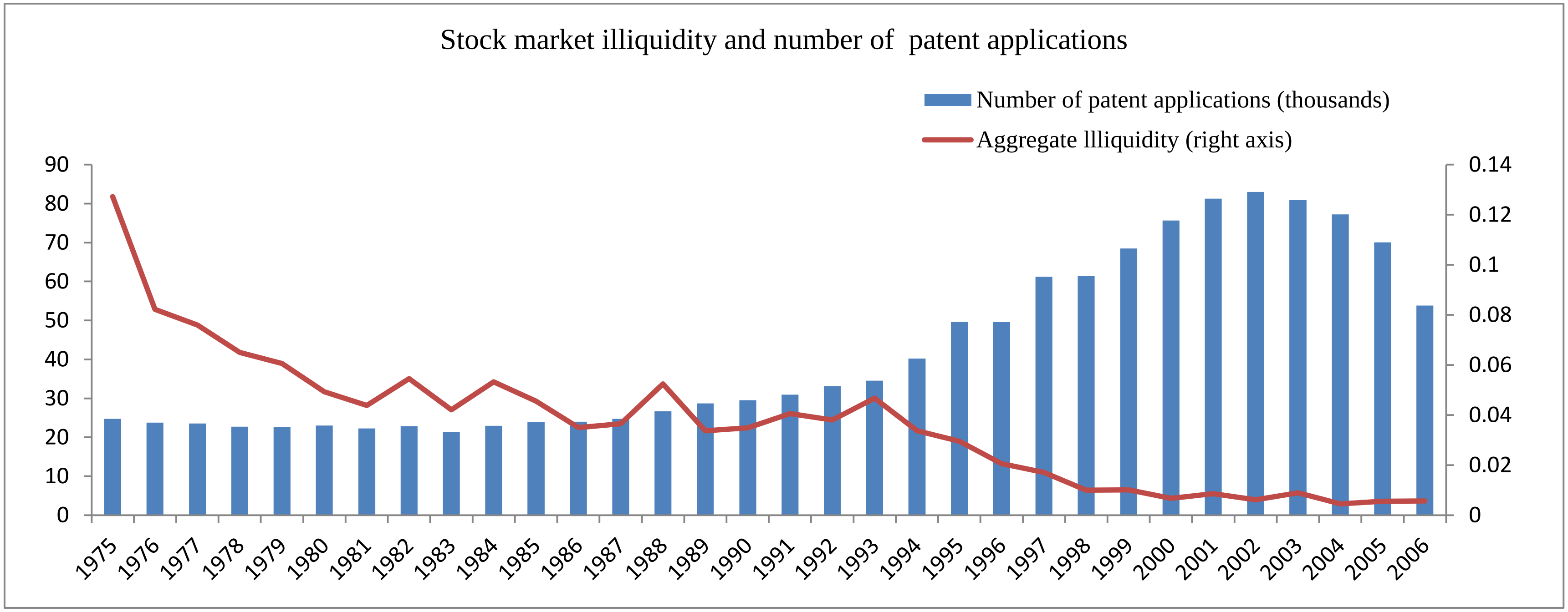

Figure 1: Stock Market Illiquidity and the Number of Patent Applications

Notes: This figure shows time-series plots of the aggregate Amihud (2002) illiquidity measure (AgLIQ) and the number of patent applications for firms with CRSP data over the period 1975 to 2006. The gray bars are the number of all patents (in thousands) in a year (the left axis). The line is the AgLIQ (the right axis). Amihud (2002) illiquidity measure is first calculated for each firm for each year. Then the value –weighted cross-sectional average for each year is calculated. More precise definition is in section II.C. Note that AgLIQ reflects illiquidity, so a high value means that stock markets are illiquid.

There are two reasons to hypothesize that stock market liquidity enhances innovation for publicly traded firms. First, several asset pricing models show that an improvement in aggregate stock market liquidity leads investors to require a lower liquidity risk premium, thus reducing the cost of equity capital. This makes it easier for firms, especially for small firms and innovative ones, to finance their innovation (see, e.g., Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Liu (2006), and Amihud, Mendelson, and Pedersen (2005)).[1] This is an important factor because, as Brown, Fazzari, and Petersen (2009) point out, "young publicly traded firms finance R&D investments almost entirely with internal or external equity. For these firms, information asymmetry, highly uncertain returns, and lack of collateral value likely make debt a poor substitute for equity finance." [2] Thus, when stock market liquidity is high, the cost of capital for investing in R&D is relatively low, allowing firms to invest more in innovation.

Second, higher stock market liquidity increases firm valuation and reduces transaction costs, which motivates large firms to buy innovation from small firms through merger and acquisition activities. On the one hand, aggregate liquidity reduces transaction costs and reallocates assets in the economy more efficiently, which results in merger waves (Harford (2005)). On the other hand, when stock markets become more liquid, the rewards of investing in R&D are high since investors would assign a higher present value to potential future cash flows generated from investing in R&D. Because the large firms cannot prevent small firms from "trying to successfully obtain the innovation first," they still have an option of buying the innovation from the small firms (Phillips and Zhdanov

[1] Butler et al. (2005) also find that both flotation costs and investment bank fees will be reduced when firm stock liquidity increases. They also suggest that stock liquidity is an important determinant of the cost of raising external equity capital.
[2] See also Atamassov et al. (2007).

(2012)). In this case, large takeover premiums are the targets' major incentive for investing in R&D. Indeed, Phillips and Zhdanov (2012) demonstrate that "an active acquisition market encourages innovation, particularly by small firms in an industry since large firms can optimally outsource R&D investment to small firms and then acquire those that successfully innovate."

My hypotheses suggest the following four testable predictions. First, aggregate innovation – as proxied by the numbers of patents[3] and aggregate R&D investments by publicly traded firms in the U.S. – should increase with aggregate stock market liquidity.[4] Next, since the effects of stock market liquidity on external financing is more pronounced for small firms or innovative ones, I hypothesize that the R&D investment sensitivity to aggregate liquidity should be stronger for small firms and firms with R&D investments. Third, if merger and acquisition activities can enhance R&D investments, merger and acquisition activities with innovation are expected to increase when stock market becomes more liquid. Finally, I expect that stock market liquidity will enhance firm innovation captured by the number of patents, patent citation and R&D investments.

In this paper, I test these predictions, using stock information from the CRSP database to calculate liquidity measures, both the number of patents granted by USPTO as well as

[3] Number of patent citations is one of the most important measures of the importance of a particular patent. However, Hall et al. (2005) document that "citation counts are inherently truncated, since patents continue to receive citations over long periods (in some cases even after 50 years)". "Moreover, patents applied for in different years suffer to different extents from this truncation bias in citations received, and hence their citation intensity is not comparable and cannot be aggregated". Thus, I only examine the effects of stock market liquidity on patent citation at the firm level.

[4] Patenting activity is considered a better proxy for innovation and R&D investments because it brings several benefits to a firm. First, it measures innovation output and captures the effectiveness of innovative processes. Second, it also enhances a firm's competitive advantage because it is hard to imitate (Lengnick-Hall (1992)). Moreover, patenting activity tends to increase firm value. Hall et al. (2005) document that innovation captured by R&D expenditures, patent count, and patent citation significantly affect the market value of a firm, "with an extra citation per patent boosting market value by 3%".

patent citation to firms in the CRSP database[5] and R&D expenditures of firms in COMPUSTAT to capture firm innovation. Because patent application is considered a better proxy for innovation, I mainly focus on the effects of aggregate liquidity on aggregate innovation captured by patenting activity in the period from 1976 to 2006[6]. I also robustly check the sample period back to 1955. Since neither the aggregate innovation level nor the liquidity of the stock market are stationary processes and neither have obvious trends, I detrend these time series before testing my predictions.

I find that stock market liquidity enhances aggregate innovation for publicly traded firms in the U.S. I also document that the relationship between aggregate liquidity and aggregate R&D expenditures is stronger for small firms, consistent with my hypothesis that small firms tend to invest more in R&D when stock markets become more liquid.

My study also shows that aggregate liquidity is significantly positively correlated with the merger and acquisition deals with patents as well as with the number of targets with patents. Furthermore, the effect of aggregate liquidity on the aggregate number of patents is stronger for large firms, which is consistent with my hypothesis that high aggregate liquidity makes it easier for large firms to buy innovation from small firms. My findings are consistent with the finding by Phillips and Zhdanov (2012) who develop a model to show that large firms optimally decide to purchase small innovative firms.

As documented in the literature, aggregate liquidity may be endogenous with aggregate innovation. I am primarily interested in the predictive power of aggregate liquidity for

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[5] I thank Kogan, Papanikolaou, Seru, and Stoffman for making the data available. The data is available at https://iu.box.com/patents.

[6] As mentioned in Hall et al. (2001, 2005, and 2009), there is the patent truncation problem at some ending years of the database. Thus, I use four year-lag of the data period to make sure that almost applied for patents are shown in the database.

aggregate innovation, but there is also the possibility of causality going in the opposite direction. I examine this issue directly by performing Granger causality tests. My results show that aggregate liquidity does Granger cause aggregate innovation growth rate but aggregate innovation growth rate does not Granger cause aggregate liquidity for the whole sample from 1976 to 2006.

In addition to the Granger causality tests, I use several methods to deal with the endogeneity problem in the relationship between aggregate liquidity and innovation. First, I exclude firms in computer and internet related industries because the development in these industries highly makes stock markets more liquid. I then examine the effects of stock market liquidity on aggregate innovation from non-computer and internet related firms. I find that this effect is stronger than the effect of aggregate liquidity on aggregate innovation for all publicly traded firms. Second, an improvement in stock market liquidity could encourage firms to issue more equity to finance their innovation projects. Thus, I expect that the effects of aggregate stock liquidity on aggregate innovation to be more pronounced for publicly traded firms than for non-publicly traded firms and other sectors. My results are consistent with this prediction.

Another important method to solve the endogeneity problem is to examine the effects of liquidity shock on firm innovation. Using a difference–in–difference methodology, Fang et al. (2013) find that the decimalization of the minimum price variation in 2001 negatively affected firm innovation. However, the underlying assumption of this model is that the macroeconomic conditions equally affect both types of firms (firms are placed into either a treatment or control group). This assumption seems incorrect because the years around decimalization 2000-2002 were the years when the tech bubble burst and

the economy slowed. During this period, innovative firms or firms in high tech industries could be more affected by the collapse of the tech bubble. Further, since the patent data is censored at zero, comparing the absolute value of the change in firm innovation seems inappropriate. For example, a treatment firm had 4 patents in 2000 and 2 patents in 2002 while control firm had 1 patent in 2000 and 0 patent in 2002. During this period, the change in innovation for a treatment firm is -2 patents and for a control firm is -1. This does not necessarily mean that a treatment firm would be less innovative than a control firm. Therefore, Dass et al. (2012) point out that the method used in Fang et al. (2013) contains some weaknesses[7] and suggest that the lag innovation should be controlled when examining the effects of liquidity on innovation. After controlling for lag innovation, Dass et al. (2012) show that liquidity is positively related with firm innovation.

Borrowing part of the methodology from Dass et al. (2012), I re-examine the effects of liquidity shock around the decimalization year of 2001 on firm innovation. I also extend this approach by investigate the effects of liquidity shock around the tick size reduction year of 1997 on the change in firm innovation from 1996 to 1998 and from 1996 to 1999. I show that the reduction in tick size enhances firm innovation.

Using panel regressions on individual firms, I further show that, after controlling for firm characteristics, stock market liquidity has a significantly positive impact on firm innovation. More interestingly, after controlling for aggregate liquidity, the effects of stock liquidity on innovation at the firm level documented in the literature (e.g. Ferreira et al. (2012), Fang et al. (2013)) becomes mixed, depending on regression specifications. As discussed by Dass et al. (2012), the results shown in Fang et al. (2013) hold only

[7] More details can be found in Dass et al. (2012)

when lag innovation is not included in the model. Thus, the cross-sectionally negative relationship between liquidity and firm innovation shown in Fang et al. (2013) could reflect that small firms, which tend to be less liquid, may be more innovative than large firms, especially when endogenous relationship between firm innovation and stock liquidity is not eliminated. Furthermore, if small firms need to be more innovative to attract large firms to buy innovation from them, this problem could also reflect that, instead of being innovative themselves, large firms (with higher stock liquidity) have an option of buying other firms' innovation (Phillips and Zhdanov (2012)).

Using the sample period from 1976 to 2002 and controlling for lag innovation, I document that firm stock liquidity is positively related to firm innovation. Further, the positive relation between firm's stock liquidity and firm innovation is more pronounced when firm innovation is captured by R&D. This evidence is consistent with Dass et al.'s (2012) findings[8].

My essay makes several contributions to the literature. First, the essay shows an important role of stock markets in innovation and economic growth. My evidence partially explains why some developed countries can generate a large number of patents and have experienced long-run economic development. Second, I document that stock market liquidity is an important determinant of firm innovation, especially for small firms and firms with R&D investments. Third, these findings suggest a channel that links stock markets to firm valuation.

[8] Dass et al. (2012) show that their results are more appropriate and robust than Fang et al.'s (2013). Moreover, because the years of decimalization 2000-2002 were years of the bursting of the "dot.com bubble", they show that the change in patent applications is strongly related to the prior level of patenting activity and "not including lagged levels would bias the results."

To the best of my knowledge, this is the first essay to examine the effect of stock market liquidity on innovation at both aggregate and firm levels. Fang et al. (2009) find that stock liquidity can increase firm performance and valuation. Hall et al. (2005) document that both patent count and patent citation significantly affects market value and an extra citation per patent can boost market value by three percent. I fill this gap by documenting that stock market liquidity can generate more innovation and, as a result, this innovation will increase firm valuation.

The recent literature (e.g. Dass et al. (2012), Ferreira et al. (2012), and Fang et al. (2013)) also examines the relation between stock liquidity and firm innovation. However, different from these papers, I measure stock liquidity at the aggregate level and focus on the effects of the market stock liquidity on aggregate innovation in the economy.

My essay is also different from the studies by Fang et al. (2013) in that I use a longer database and also deal with the patent truncation problem as well as consider the endogeneity in the innovation process. I also posit two channels by which stock market liquidity may affect firm innovation; financing and M&A activities. First, an improvement in stock market liquidity will reduce the cost of raising external capital and encourage firms, especially small firms or innovative ones, to issue more equity to finance their innovation.

Second, stock market liquidity will increase merger and acquisition activities which are substantial to push innovation. I also document that both mechanisms could drive the different effects of aggregate liquidity on aggregate innovation for each type of firms. I find that the relation between aggregate liquidity and aggregate R&D expenditures is stronger for the group of small firms due to the financing mechanism. However, the

effects of aggregate liquidity on aggregate number of patents are more pronounced for the group of large firms because high stock market liquidity makes it easier for large firms to acquire small innovative firms. Moreover, high stock market liquidity also generates large takeover premiums which create strong incentives for small firms to be innovative and eventually become takeover targets. My evidence shows that stock market liquidity play an important role in enhancing innovation, and thus suggests the link between finance and economic growth.

My essay is also related to two strands of literature: the literature on the relation between stock liquidity and cost of capital (e.g. Butler et al (2005)), and the literature on the relation between merger and acquisition and innovation (e.g. Ahuja and Katila (2001), Zhao (2009), Phillips and Zhdanov (2012), and Atanassov (2013)). Butler et al. (2005) show that stock liquidity is an important determinant of costs of raising external capital. Ahuja and Katila (2001), Phillips and Zhdanov (2011), and Atanassov (2013) document the important role of merger and acquisition activities in enhancing innovation. Moreover, Xu and Zhao (2009) find that aggregate liquidity will lead to high merger and acquisition activity. I complement and extend this literature by examining the effects of stock market liquidity on firm innovation.

The rest of the essay is organized as follows. Section 1.2 describes sample selection, variable measurement, the control variables used in empirical analysis, and descriptive statistics. Section 1.3 presents the results from the effects of stock market liquidity on aggregate innovation. The effects of stock market liquidity on raising external capital and aggregate innovation are shown in section 1.4 and these effects on merger and acquisition

activities with innovation are presented in section 1.5. Section 1.6 investigates the effects of aggregate liquidity on innovation at firm level and section 1.7 concludes.

1.2 Sample Selection, Variable Measurement, and Descriptive Statistics

1.2.1 Sample Selection

Two popular patent databases are currently publicly available, the NBER patent database and the patent database published by Kogan, Papanikolaou, Seru and Stoffman. Between them, the NBER patent database provides more detailed information on patent assignee names, the number of patents, the technological categories, the number of citations, the patent's application year and the patent's grant date, etc., from 1976 to 2006. It is valuable data used to examine firm innovation. However, in terms of aggregate patent applications, this database provides low frequency (on a yearly basis). Thus, to enrich my analysis, I prefer the patent database published by Kogan, Papanikolaou, Seru and Stoffman because it contains patent's application date from 1926 to 2010.

I collect daily stock returns, prices, volumes, and number of shares outstanding from Center of Research in Security Prices (CRSP) to calculate the Amihud (2002) illiquidity measure and the zero daily returns (ZEROS) which is developed by Lesmond et al. (1999). I include all ordinary common stocks (share code 10 and 11) traded on NYSE, AMEX, and NASDAQ from 1975 to 2006. Primes, closed-end funds, real estate investment trusts (REIT), American Depository Receipts (ADR), and foreign companies are excluded in this study. At the aggregate level, my sample period is 31 years from 1976 to 2006 with 372 months.

I collect the GDP growth rate, term structure and default spread from the Fed Reserve-St Louis. I define term structure as the difference between 10 year- Treasury bonds and 3 month –Treasury bills and the default spread as the difference between yields of Moody's BBB corporate bonds and of Moody's AAA corporate bonds. Consistent with NÆs et al. (2011), the U.S. GDP growth rate and default spread are non-stationary in the period of time from 1975 to 2006. I transform them into stationary series by simply taking the difference.

I also use COMPUSTAT files to calculate Tobin's Q, total sales, market capitalization, research and development (R&D) ratio, leverage ratio, return on assets, capital expenditure ratio, tangibility, and cash ratio. I focus on the sample period of time from 1976 to 2002 because I want to exclude the patent truncation problems from the NBER patent database[9].

Besides financial firms, utility firms are also excluded from my sample. I also exclude firms with less than 200 trading days during the previous year (y-1) and with price at the end of fiscal year less than $5. I obtain 57,477 firm year observations during the period from 1975 to 2002. I then merge this data with patent data from NBER over the period 1976 to 2002. I finally obtain 55,375 firm year observations.

1.2.2 Innovation Measures

In this paper, I examine the effects of stock market liquidity on innovation at both the aggregate and firm levels. Based on the existing literature on innovation (e.g. Hall et al. (2001 and 2005)), I use both R&D expenditures and patenting activity to measure

[9] The NBER patent database and patent truncation problems are discussed in detail in Hall, Jaffe, and Trajtenberg (2001 and 2005).

innovation. While R&D expenditures are widely used to proxy for technological innovation, they do not measure the innovation output and efficiency. Thus, following recent studies (e.g. Atanassov et al. (2007), Hsu (2011), and Fang et al. (2013)) I emphasize more on patenting activity to measure innovation.

Although patenting activity is usually used to capture innovation output, it contains two types of truncation problems. The first rises as the patents appear in the data only after they are granted. Thus, there is a significant lag between patent applications and patent grants (lately averaging about two years). As a result, only a small fraction of patent applications is shown during the last few years in the sample period. To deal with this problem, following the suggestion by Hall et al. (2005, and 2009), I exclude patent observations in the last four years of the data to make sure that almost all patent applications are filed in the data.

The second problem is that patent citation tends to increase over time because the new patent can cite an older version. This truncation bias is more obviously acute for recent patents since I observe only the first few years of citations. Moreover, patents applied for different years suffer different economic condition. Thus, it is not comparable and cannot be aggregated (Hall et al. 2005). I deal with this problem by following Hall et al. (2005) to adjust the citations for each patent until 2006 of the NBER patent database and I only use patent citations to measure innovation at firm level.

To measure aggregate innovation, I accumulate all patent applications for publicly traded firms in the U.S. from the patent database published by Kogan, Papanikolaou, Seru and Stoffman for each month from 1976 to 2006 and take this variable in logs. Over this sample period of 31 years (372 months) the changes in economic conditions and firm

structures potentially generate non-stationarity in this aggregate innovation series. Thus, to avoid the risk of obtaining spurious results, I employ the Augmented Dickey-Fuller (ADF) test with the null hypothesis that this variable has a unit root. The result shows that the null hypothesis is not rejected at 5% significant level. Therefore, I fol9low Hsu (2011) to detrend this time series by taking the difference between the value of aggregate patents (in logs) at month t and the average of all value of aggregate patents previous twelve months (one year)[10] as follow:

$$\mathrm{AgINNO_t} = \ln(\mathrm{ap}_t) - \frac{1}{12}\sum_{i=1}^{12}\ln(ap_{t-i}) \qquad (1)$$

where $\mathrm{ap_t}$ is the number of total patent applications of firms shown in CRSP in month t.

I also use the aggregate R&D expenditures to proxy for aggregate innovation. However, because patenting activity is considered a better measure to proxy for innovation, I only use aggregate R&D expenditures to capture innovation when I examine the relation between it and aggregate liquidity for groups of firms with different sizes. I simply detrend this variable by taking the difference of the log of its values.

At firm level, I employ the log of number of patents scaled by size, the number of patents, the adjusted number of patent citations per patent scaled by size, as well as the adjusted number of patent citations per patent, and the ratio of R&D expenditures to total assets to capture firm innovation. These variables are widely used in current literature (e.g. Hall et al. (2005), and Atanassov et al. (2007)).

[10] My results are consistent when I use a detrending method at different time intervals such as taking the difference between the value of aggregate number of patent applications this month and the average of all number of patent applications over the previous 6 months or18 months.

1.2.3 Liquidity Measures

Although there are numerous studies on liquidity, the liquidity concept itself is still unclear and ambiguous (Cholette et al. (2007)) because it comprises of several dimensions including trading costs, turnover, bid-ask spreads, and price impact. To capture this idea, current finance literature generally considers liquidity as the ability to trade large quantities quickly at low cost with little price impact (Liu (2006) and Chordia et al. (2009)). Although this definition of multi-dimensional liquidity is generally accepted, a single liquidity measure may not capture all dimensions of liquidity (Cholette et al., (2007)).

Because this essay examines the effects of stock market liquidity on innovation and investigates whether an increase in stock market liquidity can reduce the cost of raising equity, I prefer a liquidity measure which is priced. I mainly use Amihud (2002) illiquidity measure since it has some advantages. First, it can be computed using daily data and thus allows me to study a much longer period of time. Second, it corresponds to the concept of price impact and is priced. Third, it is highly correlated with other liquidity measures such as bid-ask spread, trading volume, and other price impact measures (e.g. Geyenko et al. (2009)). Fourth, it is also highly correlated with a common systematic component of liquidity and is widely used to measure liquidity at both aggregate and firm levels (e.g. Acharya and Pedersen (2006), Kamara et al (2008), and Geyenko et al. (2009)).

Amihud (2012) illiquidity measure ($ILLIQ_{i,y}$) is calculated as follow:

$$ILLIQ_{i,y} = \frac{1}{D_{i,y}} \sum_{t=1}^{D_{i,y}} \frac{|R_{i,t}|}{P_{i,t} \times Vol_{i,t}} \quad (2)$$

where $D_{i,y}$ is the number of valid observation days for stock i in during year y, $|R_{i,t}|$ is the absolute return on day t for security i. $P_{i,t}$, and $VOL_{i,t}$ are respectively the daily price, and trading volume of stock i on day t. Because the value of ILLIQ calculating from (2) is very tiny, it is standard to multiply the above estimate by 10^6 for practical purposes. This measure is called an illiquidity measure because a high value indicates low liquidity.

Another liquidity measure used in my essay is zero daily returns (ZEROS) which is developed by Lesmond, Ogden, and Trzcinka (1999). It is also widely used in current literature (e.g. Bekaert et al. (2007), and Goyenko et al. (2009)). It is computed as the proportion of number of days with zero returns to the number of trading days in a year.

I follow Amihud (2002) and exclude the firms with less than 200 trading days during the year y and with stock prices less than \$5 at the end of year y. I also require firms to have trading volume and market capitalization in year y to calculate the Amihud (2002) illiquidity measure.

Because the impact of a firm on the stock markets depends on its size, I compute aggregate liquidity measures by using the value-weighted average method[11]. Due to the nonstationary nature of the time series of both the aggregate Amihud (2002) illiquidity measure and zero daily returns, I follow Kamara et al. (2008) and NÆs et al. (2011) to detrend these time series by using the change in these liquidity measures (in logs) as my illiquidity measures. Specifically, I define these illiquidity measures as follow:

$$AgILLIQ_t = \log(AMILLIQ_t / AMILLIQ_{t-1}), \text{ and}$$

$$AgZERO_t = \log(AZERO_t / AZERO_{t-1}) \quad (3)$$

[11] My results are consistent when I use equally-weighted average method to calculate aggregate stock liquidity measures.

where $AMILLIQ_t$ is the aggregate Amihud (2002) illiquidity measure at time t and $AZERO_t$ is the aggregate zero daily returns.

Table 1: Correlations between Aggregate Variables

	NAgINNO	AgINNO	AgILLIQ	AgZERO	dGDP	Term
AgINNO	0.551					
	(0.00)					
AgILLIQ	-0.090	0.005				
	(0.08)	(0.93)				
AgZERO	-0.089	0.007	0.228			
	(0.08)	(0.89)	(0.00)			
dGDP	0.114	-0.035	-0.026	-0.071		
	(0.03)	(0.50)	(0.61)	(0.17)		
Term	-0.017	0.018	0.077	0.187	0.070	
	(0.73)	(0.73)	(0.14)	(0.00)	(0.18)	
Cdefault	0.024	0.133	0.065	0.011	-0.154	-0.134
	(0.64)	(0.01)	(0.21)	(0.83)	(0.00)	(0.01)

Notes: This table shows the Pearson correlation between the variables used in the analysis in my paper. The associated p-values are reported in parentheses below each correlation coefficient. (N)AgINNO is the detrended aggregate number of patents (next year). AgILLIQ is the detrended aggregate Amihud (2002) illiquidity measure, and AgZERO the detrended aggregate number of zero daily returns. The cross-sectional illiquidity measures (AgILLIQ and AgZERO) are calculated as a weighted average across stocks and then are detrended. dGDP is the change in GDP growth rate, Term is term structure and Cdefault is the change in default spread.

Table 1 presents the correlations between the detrended aggregate variables used in my analysis. This table shows that the two illiquidity measures are significantly correlated with each other and that they are also negatively correlated with the aggregate innovation captured by the number of patents next year. Table 1 shows that the GDP growth rate is positively related with the aggregate innovation next year but insignificantly correlated with the current innovation level. Moreover, term structure and default spread are not correlated with aggregate innovation next year. These results show that there is a lag in innovation activities and that stock markets play an important role in generating

innovation, consistent with the current studies (Hall et al. (2009), and Brown at el. (2009)).

1.2.4 Control Variables and Descriptive Statistics

To examine the effects of aggregate liquidity on innovation at firm level, I follow the current literature on innovation and liquidity to control for a set of firm and industry characteristics that may affect a firm's future innovation. Specifically, my control variables include Tobin's Q, size, total debt ratio, return on assets, capital expenditure ratio, tangibility, firm age, cash ratio, R&D expenditure to total assets, and firm stock liquidity. I calculate the Tobin's Q as the ratio of market value of equity plus book value of total assets minus book value of equity minus deferred taxes to book value of total assets. Size is the natural logarithm of total market value of equity, capital expenditure ratio is the ratio of capital expenditures to sales, tangibility is the ratio of net property, plant and equipment (PPE) to total assets and firm age is the natural logarithm of one plus the firm age in COMPUSTAT. Total debt ratio is the ratio of both short term and long term debt to total book value of total assets, while cash is cash and short term investments scaled by total assets. Return-on-assets ratio is calculated as operating income before depreciation divided by book value of total assets. I use both the Amihud (2002) illiquidity measure and zero daily returns to capture firm stock liquidity. In my analysis, all firm characteristics are computed for each firm over its fiscal year y. I also use the Herfindahl index (HHI) based on annual sales to proxy for industry product market competition and the KZ index to capture firm's financial constraints. These variables are defined in detail in table 2.

Table 2: Variable Definitions

Variable	Definition
lpatent	The natural logarithm of one plus firm i’s total number of patent application in year t
lpatents	The natural logarithm of one plus firm i’s total number of patent application scaled by firm size in year t
lpcite	The natural logarithm of one plus firm i’s adjusted number of patent citations per patent. The adjustment methods are shown in Hall et al. (2005).
lpcites	The natural logarithm of one plus firm i’s adjusted number of patent citations per patent scaled by size in year t
RDAT	R&D expenditure (#46) scaled by the book value of total assets (#6) measured at the end of fiscal year *t*, set to 0 if missing
Q	Tobin’s Q, calculated as [market value of equity (#199×#25) plus book value of assets (#6) minus book value of equity (#60) minus balance sheet deferred taxes (#74, set to 0 if missing)] divided by book value of assets (#6)
LSIZE	Natural logarithm of firm *i*'s total market value of equity (#25×#199) measured at the end of fiscal year *t*
totaldebt	Firm *i*’s total debt ratio, measured as book value of total debt (#9+#34) divided by book value of total assets (#6) measured at the end of fiscal year *t*
ROA	Return-on-assets ratio computed as operating income before depreciation (#13) divided by book value of total assets (#6), measured at the end of fiscal year *t*
CAPX	Capital expenditure (#128) scaled by sales (#12) measured at the end of fiscal year *t*
TANG	Net property, Plant & Equip (#8) divided by book value of total assets (#6) measured at the end of fiscal year *t*
CASH	Cash and short term investments (#1) scaled by book value of total assets (#6) measured at the end of fiscal year *t*
LAGE	Natural logarithm of one plus firm *i*'s age, approximated by the number of years listed on Compustat
ISSEQUITY	Equity issuance of firm i in year t+1, calculated by the difference between Sale of Common and Preferred Stock (#108) and Purchase of Common and Preferred Stock (#115) scaled by total assets (#6) in previous year

Table 2: Variable Definitions (continued)

Variable	Definition
ISSDEBT	Debt issuance of firm i in year t+1, computed as long term debt issuance (#111) minus long term debt reduction (#114), plus changes in current debt (#301) scaled by total assets (#6) in previous year
HHI	Herfindahl index of 4-digit SIC industry *j* where firm *i* belongs, measured at the end of each year *t*
KZINDEX	The KZ-index of firm i measured at the end of fiscal year t, computed as -1.002 * Cash flow ((#18+#14)/#8) + 0.283 * Q plus 3.139x leverage ((#9 + #34)/(#9+ #34 +#216)) - 39.368 * Dividends ((#24 +#19)/38) minus 1.315 * Cash holding (#1/#8, where #8 is lagged).

Table 3: Descriptive Statistics

Variable	5%	25%	Median	Mean	75%	95%	N
lpatent	0.000	0.000	0.000	0.603	0.693	3.178	55,375
lpcite	0.000	0.000	0.000	0.657	1.429	2.998	55,375
ILLIQ	0.001	0.013	0.089	0.640	0.493	3.070	55,375
ZERO	0.028	0.099	0.167	0.178	0.244	0.352	55,375
Q	0.799	1.036	1.358	1.930	2.041	4.826	55,375
LSIZE	2.939	4.171	5.242	5.441	6.540	8.576	55,375
totaldebt	0.000	0.067	0.206	0.220	0.333	0.539	55,375
ROA	-0.066	0.093	0.145	0.133	0.199	0.298	55,375
CAPX	0.008	0.026	0.048	0.286	0.095	0.391	55,375
TANG	0.049	0.157	0.276	0.322	0.445	0.762	55,375
RDAT	0.000	0.000	0.000	0.035	0.037	0.162	55,375
CASH	0.004	0.022	0.065	0.139	0.183	0.541	55,375
HHI	0.056	0.115	0.191	0.239	0.307	0.621	55,375
LAGE	1.609	2.079	2.773	2.721	3.332	3.738	55,375

Notes: This table reports the summary statistics for variables used to analyze the effects of aggregate liquidity on firm innovation. The sample period is from 1976 to 2002. lpatent and lpcite are respectively the logarithm of one plus the number of patents and of one plus the number of citations per patent for each firm. ILLIQ and ZERO are the Amihud (2002) illiquidity and zero daily return measures. Q, LSIZE, totaldebt, ROA, CAPX, TANG, RDAT, and CASH are respectively Tobin's Q, logarithm of market capitalization, total debt ratio, return on assets, capital expenditure ratio, tangible assets ratio, R&D expenditures to total assets, and cash holding ratio. HHI is the Herfindahl index, and LAGE is logarithm of one plus firm age.

Table 3 provides summary statistics of firm variables used in my analysis. On average, a firm in my sample acquires 0.83 patents per year and each patent was cited 2.53 times. The Amihud (2002) illiquidity measure has a mean value of 0.640 and the mean value of zero daily returns is 0.178. The average market capitalization of firms in my sample is $1.63 billion and each firm invests 3.48% total assets in R&D on average. This table also shows that an average firm has ROA of 13.32%, total debt ratio of 20.03%, PPE ratio of 32.22%, cash ratio of 13.90%, and is 14.20 years old.

1.3 Stock Market Liquidity and Aggregate Innovation

1.3.1 In- sample Evidence

An important issue in investigating innovation is the time lag between input and output of this process. Stoneman (1983) argued strongly that patents are an input to the R&D process rather than its output. That is because firms tend to file their patent at the beginning of an innovation process. Consistent with this argument, Hall, Griliches and Hausman (1986) find that R&D investments contemporaneously affect patenting activity but the "contribution of R&D history to the current year's patent applications is quite small". Recently, Gurmu and Perez-Sebastian (2007) document that "the contemporaneous relationship between patenting and R&D expenditures continues to be strong, accounting for over 60% of total R&D elasticity." Further, Gurmu and Perez-Sebastian (2007) show that the time-lag between R&D and patenting becomes shorter over time. Thus, it is reasonable to examine the effects of stock market liquidity on aggregate innovation next year. I will also robustly extend the time gap in the next section.

As shown in the previous section, future aggregate innovation is positively correlated with the current stock market liquidity level. In this section, I examine the ability of aggregate liquidity to predict future aggregate innovation by considering the following regression model[12]:

$$AgINNO_{t+12} = \alpha + \beta AILLIQ_t + \gamma X_t + \varepsilon_{t+12} \qquad (4)$$

Where $AgINNO_{t+12}$ is the aggregate innovation growth rate captured by the aggregate number of patent applications in month t+12 (one year later), $AILLIQ_t$ is aggregate stock market liquidity measures captured by aggregate Amihud (2002) illiquidity and zero daily returns measure by Lesmond, Ogden, and Trzcinka (1999) at month t. X_t is a vector of control variables (change in GDP growth rate (dGDP), term and change in default spread (cdefault), and the current aggregate innovation growth rate ($AgINNO_t$) at month t.

Table 4 reports the results from the various regression specifications from the above model. The first specification includes only one of the liquidity measures and the lag of aggregate innovation. Both panel A and B of this table show that both liquidity measures are significantly correlated with future aggregate innovation captured by aggregate number of patent applications. The coefficient of Amihud (2002) illiquidity measure is -0.184 and its t-statistic is 2.99, while the coefficient of zero daily returns is -0.474 and its t-statistic is 2.54. This implies that an increase in stock market liquidity predicts a higher aggregate innovation growth rate.

[12] My results are consistent when I control for aggregate capital inflows and outflows, unemployment rate and fed funds.

It is useful to interpret these coefficients to comprehend the magnitude of the estimated effects. My sample shows that the standard deviation of change in Amihud (2002) illiquidity (AgILLIQ) is 0.072 and of change in aggregate zero daily returns (AgZERO) is 0.028. Thus, for one standard deviation increase in AgILLIQ or in AgZERO, the aggregate innovation growth rate will decrease by 1.32%. During the sample period, the average aggregate innovation growth rate is 1.30%. Thus, this predicted change in aggregate innovation growth rate is more than the average growth rate in aggregate innovation.

Table 4: Stock Market Illiquidity and Aggregate Innovation

Panel A: Amihud (2002) Illiquidity

Model	(1) $AgINNO_{t+12}$	(2) $AgINNO_{t+12}$	(3) $AgINNO_{t+12}$	(4) $AgINNO_{t+12}$
Intercept	0.001	0.001	0.007	0.008
	(0.21)	(0.18)	(0.77)	(0.84)
$AgILLIQ_t$	-0.184***	-0.178***	-0.173***	-0.169***
	(-2.99)	(-2.90)	(-2.82)	(-2.80)
$AgINNO_t$	0.566***	0.571***	0.571***	0.575***
	(6.43)	6.53	6.50	(6.45)
$dGDP_t$		1.990***	2.024***	1.962***
		2.92	(2.95)	(2.98)
$Term_t$			-0.003	-0.004
			(-0.76)	(-0.84)
$Cdefault_t$				-0.037
				(-0.78)
N	372	372	372	372
Adj R-square	0.3090	0.3245	0.3236	0.3225

Table 4: Stock Market Illiquidity and Aggregate Innovation (continued)
Panel B: Zero Illiquidity (monthly data)

Model	(1) $AgINNO_{t+12}$	(2) $AgINNO_{t+12}$	(3) $AgINNO_{t+12}$	(4) $AgINNO_{t+12}$
Intercept	0.000	0.000	0.005	0.006
	(0.05)	(0.06)	(0.49)	(0.57)
$AgZERO_t$	-0.474**	-0.428**	-0.406**	-0.402**
	(-2.54)	(-2.30)	(-2.08)	(-2.07)
$AgINNO_t$	0.566***	0.571***	0.571***	0.576***
	(6.48)	(6.57)	(6.54)	(6.50)
$dGDP_t$		1.935***	1.963***	1.892***
		(2.80)	(2.81)	(2.83)
$Term_t$			-0.002	-0.003
			(-0.52)	(-0.62)
$Cdefault_t$				-0.042
				(-0.89)
N	372	372	372	372
R-square	0.3090	0.3235	0.3221	0.3214

Notes: This table reports the results from the regression models of aggregate innovation on aggregate liquidity measure and other macro variables last 12 months for the period 1976 to 2006. $AgINNO_{t+12}$ is aggregate innovation captured by the number of patent applications next year (12 months). $AgILIQ_t$ and $AgZERO_t$ are respectively the aggregate Amihud (2002) illiquidity and zero daily return measures at month t. $dGDP_t$, $Term_t$, $Cdefault_t$ and are respectively the change in GDP growth rate, term structure, and the change in default spread. Panel A shows the effects of aggregate Amihud (2002) illiquidity on aggregate patent, and Panel B shows the effects of zero daily return measure on aggregate patent. The Newey-West corrected t-statistics are reported in the parentheses. ***, and ** denotes a rejection of the null hypothesis at the 1% and 5% level, respectively.

Other macroeconomic variables may contain information about future aggregate innovation. I therefore consider the effects of aggregate liquidity on future innovation after controlling for some main macroeconomic variables. I choose some main variables which are widely used in the current literature: GDP growth rate, term structure and default spread. While GDP growth rate can capture the general macroeconomic condition, term structure and default spread can capture the debt market condition. I then run the regression specifications in which I control for these variables.

The results in table 4 show that aggregate liquidity measures (AgILLIQ and AgZERO) are still significantly correlated with future aggregate innovation growth rate. Moreover, GDP growth rate is an important factor in predicting future innovation while term structure and default spread are not significantly correlated with the aggregate innovation growth rate in the future. My results indicate that general macroeconomic conditions and the stock market play important roles in enhancing firms to innovate in future. These results are consistent with recent studies (e.g. Atanassov et al. (2007), Hall et al. (2009), and Brown et al. (2009)). Atanassov at al. (2007) find that public firms prefer equity and public debt to bank debt to finance their innovation. Brown et al. (2009) document that the U.S. firms finance their R&D from two main sources: cash flow and stock issues.

Overall, my study shows that stock market liquidity contains economically significant information about future aggregate innovation. When the stock market liquidity improves, the aggregate innovation will be enhanced, and vice versa.

1.3.2 Robustness Tests

In the previous section, I allow a one year gap between aggregate stock market liquidity and aggregate information. Although both Hall et al. (1986) and Gurmu and Perez-Sebastian (2007) document the significant impact of contemporaneous R&D investments on patenting, they differently show the effects of lag R&D on patent application. While Hall et al. (1986) show that these effects are very small, Gurmu and Perez-Sebastian (2007) note that lag R&D elasticity of patents may account for 40% of total R&D elasticity of patents. Thus, in this section, I will extend the time gap between aggregate stock market liquidity and aggregate innovation to 18 months or 2 years. I first re-detrend

the aggregate number of patent application to reflect the time gap and then conduct the test using model (4). The results are shown in table 5.

Table 5 shows that both aggregate illiquidity measures are significantly correlated with aggregate innovation next eighteen months, even after controlling for some macro variables. The coefficient of aggregate Amihud (2002) illiquidity proxy is -0.150 with its t-statistic value of -2.46. Similarly, the t-statistic of the coefficient of aggregate zero daily returns is -2.19, which is significant at 5% significance level. This result still holds when I extend the time gap between aggregate stock market liquidity and aggregate innovation to 2 years (not reported).

I also robustly test the effect of aggregate stock market liquidity on aggregate innovation by using a vector auto-regression (VAR) methodology. The benefit of this method is to control for other endogenous variables which may affect both aggregate stock market liquidity and aggregate innovation. In particular, I use the following model:

$$Y_t = c + \Psi_{t-1}Y_{t-1} + \Psi_{t-2}Y_{t-2} + \ldots + \Psi_{t-p}Y_{t-p} + \varepsilon_t \quad (5)$$

Where Y = (AgINNO, AILLIQ, dGDP, Term, Cdefault) denotes a (4×1) vector of time series variables, Ψ_i are (4×4) coefficient matrices and ε_t is a (4×1) vector of noise errors.

I run model (5) with p from 12 to 24 (months). The results (not reported) show that both the aggregate stock market liquidity measures are significantly correlated with aggregate innovation. These results support my hypothesis that stock market liquidity enhances innovation activity at the aggregate level.

Table 5: Stock Market Illiquidity and Aggregate Innovation next eighteen months

Model	(1) $AgINNO_{t+18}$	(2) $AgINNO_{t+18}$	(3) $AgINNO_{t+18}$	(4) $AgINNO_{t+18}$
Intercept	0.001	0.006	0.000	0.003
	(0.21)	(0.66)	(0.05)	(0.32)
$AgILLIQ_t$	-0.184***	-0.150**		
	(-2.99)	(-2.46)		
$AgZERO_t$			-0.474**	-0.432**
			(-2.54)	(-2.19)
$AgINNO_t$	0.566***	0.571***	0.566***	0.571***
	(6.43)	(6.60)	(6.48)	(6.66)
$dGDP_t$		1.989***		2.050***
		(3.16)		(3.25)
$Term_t$		-0.003		-0.002
		(-0.63)		(-0.36)
$Cdefault_t$		0.003		0.001
		(0.11)		(0.05)
N	372	372	372	372
Adj R-square	0.3090	0.3254	0.3090	0.3268

Notes: This table reports the results from the regression models of aggregate innovation on aggregate liquidity measure and other macro variables last 18 months for the period 1976 to 2006. $AgINNO_{t+18}$ is aggregate innovation captured by the number of patent applications next 18 months. $AgILIQ_t$ and $AgZERO_t$ are respectively the aggregate Amihud (2002) illiquidity and zero daily return measures at month t. $dGDP_t$, $Term_t$, $Cdefault_t$ and are respectively the change in GDP growth rate, term structure, and the change in default spread. The Newey-West corrected t-statistics are reported in the parentheses. ***, and ** denotes a rejection of the null hypothesis at the 1% and 5% level, respectively.

1.3.3 Causality

1.3.3.1 Granger Causality Tests

Current literature debates the relation between firm stock liquidity and firm innovation. However, the results are mixed. On the one hand, Fang et al. (2013) find that firm stock liquidity will impede its innovation. On the other hand, Dass et al. (2012) document that innovative firms have higher liquidity and that they take a variety of actions to keep their stocks liquid. Nevertheless, there is no study examining this relation at aggregate level.

To my best knowledge, I am the first to investigate the relation between aggregate liquidity and innovation at both the aggregate and firm levels. I am primarily interested in the predictive power of aggregate liquidity for aggregate innovation, but there is also the possibility of causality going in the opposite direction, with the change in aggregate innovation growth rate affecting stock market liquidity. I examine this issue directly by performing Granger causality tests. As analyzed in the previous section, some macroeconomic variables can affect both aggregate innovation and aggregate liquidity, I control for these variables in running Granger causality tests.

An important note about Granger causality test is that the results depend on the lag length. Thus, I require that the lag is long enough to reflect the effects of past values of these time series on their current values. I also use the log likelihood and AICC criteria to choose the right lag length. I then perform the tests using a VAR framework. These tests are conducted for the whole sample and for subsamples.

Table 6 shows the results from these tests. In the first part of Panel A and B, the null hypothesis is that aggregate liquidity measures (AgILLIQ and AgZERO) do not Granger cause aggregate innovation growth rate (AgILLIQ $\nrightarrow$ dAgINNO and AgZERO $\nrightarrow$ dAgINNO). This null hypothesis is rejected at 1% level for aggregate Amihud (2002) liquidity measure and for aggregate zero daily returns (AgZERO) in subsamples. For the whole sample period, this hypothesis is rejected at 5% level for aggregate zero daily returns (AgZERO). These results imply that stock market liquidity does Granger cause innovation at aggregate level.

Table 6: Granger Causality Tests

Panel A: ILLIQ

	Whole sample	First Haft	Second Haft
	1975-2005	1975-1990	1991-2005
H_0: dAgILLIQ $\nrightarrow$ dAgINNO			
χ^2	144.46***	160.16***	132.71***
P-value	0.00	0.00	0.00
H_0: dAgINNO $\nrightarrow$ dAgILLIQ			
χ^2	87.72	138.97***	71.11
P-value	0.71	0.00	0.97
N	372	192	180

Panel B: ZERO

	Whole sample	First Haft	Second Haft
	1975-2005	1975-1990	1991-2005
H_0: dAgZERO $\nrightarrow$ dAgINNO			
χ^2	126.10**	177.63***	132.11***
P-value	0.02	0.00	0.00
H_0: dAgINNO $\nrightarrow$ dAgZERO			
χ^2	122.18**	157.17***	103.26
P-value	0.04	0.00	0.29
N	372	192	180

Notes: This table shows Granger causality tests between aggregate innovation (detrended) and (a) the detrended aggregate Amihud (2002) illiquidity measure and (b) zero daily return measure. The test is performed for the whole sample period and different sub-periods. For each illiquidity measure, I first test the null hypothesis that illiquidity does not Granger cause the aggregate innovation. I report χ^2 and P-value for each test. I choose the optimal lag length based on the log likelihood and AICC criteria. ***, and ** denotes a rejection of the null hypothesis at the 1% and 5% level, respectively.

An interesting point in these results is that aggregate innovation growth rate does not Granger cause aggregate liquidity for the whole sample and for the period of time from 1990 to 2006. However, it Granger causes aggregate liquidity for the period of time from 1975 to 1990. This may be a result of the relatively weak power of institutional investors and/or the high volume of M&A activities at that time.

1.3.3.2 Aggregate Liquidity, Aggregate Innovation and Technological Categories

In the previous section, I conducted the Granger causality tests to examine the causality problem between aggregate stock market liquidity and aggregate innovation. Because endogeneity is a serious problem in empirical finance (Roberts and Whited (2012)), I consider some other methods to deal with it. Since the technological development such as in computers and internet industries can make the stock markets more liquid, I exclude firms in these industries to test the effects of stock market liquidity on aggregate innovation.

I follow Fama and French (1997) to define computer and internet related industries as the industries with the following four-digit SIC codes 3660 to 3692, 3695 to 3699, 3810 to 3839, 4800 to 4899, 7370 to 7373 and 7375. I first accumulate all patent applications for firms in the remaining industries, then I regress this aggregate innovation on aggregate liquidity and other macro variables.

The results in table 7 present that aggregate stock market liquidity is significantly related to aggregate innovation. This result is consistent when firms in high tech industries are excluded[13]. The coefficient of aggregate Amihud (2002) proxy in the first model is -2.06 with its t-statistic of 3.20. Similarly, the coefficient of aggregate zero daily returns is -0.563 with its t-statistic of -2.78. The absolute values of these figures are greater than those in table 4, implying that the effect of aggregate stock market liquidity on aggregate innovation is more pronounced for firms in non- computer and internet related industries.

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[13] High tech industries are those with the following four-digit SIC codes from 3570 to 3579, 3600 to 3629, 3640 to 3646, 3648 to 3649, 3660 to 3692, 3695 to 3699, 4800 to 4899, 7370 to 7373 and 7375.

Table 7: Aggregate Illiquidity and Aggregate Innovation of Firms in Non-computer and Internet related Industries

Model	(1) $AgINNO_{t+12}$	(2) $AgINNO_{t+12}$	(3) $AgINNO_{t+12}$	(4) $AgINNO_{t+12}$
Intercept	0.001	0.008	0.000	0.004
	(0.17)	(0.77)	(-0.02)	(0.37)
$AgILLIQ_t$	-0.206***	-0.170***		
	(-3.20)	(-2.67)		
$AgZERO_t$			-0.563***	-0.516**
			(-2.78)	(-2.41)
$AgINNO_t$	0.513***	0.518***	0.515***	0.520***
	(5.83)	(5.98)	(5.90)	(6.06)
$dGDP_t$		1.981***		2.047***
		(2.99)		(3.09)
$Term_t$		-0.004		-0.002
		(-0.78)		(-0.47)
$Cdefault_t$		0.003		0.001
		(0.11)		(0.05)
N	372	372	372	372
Adj R-square	0.2589	0.2749	0.2604	0.2776

Notes: This table shows the results from the regression models of aggregate innovation of firms in non-computer and internet related industries on aggregate liquidity measure and other macro variables last 12 months for the period 1976 to 2006. $AgINNO_{t+12}$ is aggregate innovation captured by the number of patent applications next year (12 months). $AgILIQ_t$ and $AgZERO_t$ are respectively the aggregate Amihud (2002) illiquidity and zero daily return measures at month t. $dGDP_t$, $Term_t$, $Cdefault_t$ and are respectively the change in GDP growth rate, term structure, and the change in default spread. The Newey-West corrected t-statistics are reported in the parentheses. ***, and ** denotes a rejection of the null hypothesis at the 1% and 5% level, respectively.

1.3.3.3 Publicly Traded Firms versus Non-publicly Traded Firms and Other Sectors

In this paper, I hypothesize that aggregate liquidity will enhance innovation because it can reduce the cost of equity issuance and encourage merger and acquisition activities. Since non-publicly traded firms and other institutions do not directly use stock markets to raise their capital, I expect that the effects of aggregate liquidity on their innovation are much weaker. I use both the aggregate number of patent application of non-publicly traded firms and other sectors and R&D investments of private firms to capture innovation.

Similar to the previous sections, I accumulate all monthly patent applications for non-publicly traded firms and other institutions in the U.S. from the patent database published by Kogan et al. (2012) from 1976 to 2006 and take this variable in logs. I also aggregate all yearly R&D expenditures for non-publicly traded firms from COMPUSTAT in the same period. I then use model (4) to regress these aggregate innovation variables on aggregate liquidity and other control macro-variables. The results are reported in table 8.

Table 8: Aggregate Liquidity and Innovation of Non-publicly Traded Firms

	(1) $AgINNO_{t+12}$	(2) $AgINNO_{t+12}$	(3) $AgRD_t$	(4) $AgRD_t$
Intercept	0.008	0.007	0.068	0.121
	(0.86)	(0.70)	(0.78)	(1.33)
$AgILLIQ_t$	-0.080		-0.016	
	(-1.49)		(-0.10)	
$AgZERO_t$		-0.176		0.274
		(-1.03)		(1.49)
$AgINNO_t$	0.377***	0.379***		
	(4.19)	(4.22)		
$AgRD_{t-1}$			0.049	0.035
			(0.24)	(0.18)
$dGDP_t$	1.961***	1.931***	-3.888	-6.062
	(2.76)	(2.67)	(-0.57)	(-0.93)
$Term_t$	-0.002	-0.001	0.032	0.014
	(-0.42)	(-0.32)	(0.79)	(0.34)
$Cdefault_t$	-0.071	-0.073	0.113	0.071
	(-1.43)	(-1.48)	(0.810	(0.52)
N	372	372	31	31
R -square	0.1687	0.1653	0.0537	0.1304

Notes: This table shows the results from the regression models of aggregate innovation of non-publicly traded firms on aggregate liquidity measure and other macro variables last 12 months for the period 1976 to 2006. $AgINNO_{t+12}$ is aggregate innovation captured by the number of patent applications next year (12 months). $AgRD_t$ is aggregate R&D expenditures. $AgILIQ_t$ and $AgZERO_t$ are respectively the aggregate Amihud (2002) illiquidity and zero daily return measures at month t. $dGDP_t$, $Term_t$, $Cdefault_t$ and are respectively the change in GDP growth rate, term structure, and the change in default spread. The Newey-West corrected t-statistics are reported in the parentheses. ***, and ** denotes a rejection of the null hypothesis at the 1% and 5% level, respectively.

Consistent with my prediction, this table shows that both aggregate liquidity measures do not significantly affect aggregate innovation. T-statistics of the coefficients of AgILLIQ and AgZERO are less than 1.50. The results from this table also show that while GDP growth rate is significantly correlated with aggregate innovation captured by aggregate number of patent application, it is not significantly related to aggregate R&D investments.

1.3.3.4 Liquidity Shock and Innovation

An important method to deal with the endogeneity problem in the relationship between liquidity and innovation is to examine the effect of an exogenous shock to stock liquidity on firm innovation. Using a difference–in–difference methodology, Fang et al. (2013) find that the decimalization of the minimum tick size in 2001 negatively affects firm innovation. However, the underlying assumption of this model is that the macroeconomic conditions equally affect both types of firms (firms are designated as either control or treatment). This assumption seems incorrect because the years around decimalization during 2000-2002 were the years in which the tech bubble bursts. During this period, innovative firms or firms in high tech industries could be more affected by the burst of the technology bubble. Furthermore, since the patent data is censored at zero, comparing the change in innovation among the firms may not be correct. Therefore, Dass et al. (2012) point out that the method used in Fang et al. (2013) contains some weaknesses and suggest that the lag innovation should be controlled when examining the effects of liquidity on innovation. After controlling for lag innovation, they document a positive relation between liquidity and innovation.

I first re-examine the effects of an endogenous shock to liquidity around the decimalization year of 2001 on firm innovation. Before 2000, the minimum price variation for quotes and trades on three major U.S. exchanges was $1/16. Over the period of August 28, 2000 to January 29, 2001, the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) reduced the minimum tick size to pennies. The NASDAQ adapted this policy over the interval of March 12, 2001 to April 09, 2001. Following Fang et al. (2013) and Dass et al. (2012), I consider the decimalization year of 2001 as year of liquidity shock, and investigate the effects of the change in firm stock liquidity from 2000 to 2002 on the change in firm innovation from 2000 to 2002 or from 2000 to 2003.

Panel A of table 9 shows that the change in firm stock liquidity is positively related with the change in firm innovation. This means that after controlling for some firm characteristics, an improvement in stock liquidity will enhance firm innovation. The T-statistics of the coefficients of change in stock illiquidity captured by Amahud (2002) and zero daily return ratio are from -3.25 to -1.83. This result shows that the shock to stock liquidity in 2001 enhanced firm innovation.

The results in table 9 present that lag innovations are negatively correlated with the change in innovation for firms from 2000 to 2002. The T-statistics of the coefficients of lag patent application or lag patent citation are from -15.93 to -15.60. These results are consistent with Dass et al.'s (2012) suggestions.

Panel A of table 9 also shows that larger firms or firms with higher R&D investments will have more patent application with higher citation. In contrast, firms with high capital expenditures will obtain less patent application as well as less citation per patent.

Interestingly, the results in table 9 present that firm's total assets and leverage do not affect the change in firm innovation from 2000 to 2002.

I extend this finding by examining the effects of another shock to stock liquidity on firm innovation: the effect of tick size reduction in 1997. On March 13, 1997 the American Stock Exchange (AMEX) adapted the new tick size of sixteenth for all stocks. Shortly later, the NASDAQ board approved quotes in 1/16 on March 25. On June 24, 1997 the New York Stock Exchange (NYSE) declined the minimum tick size for quoting and trading stocks from an eighth to a sixteenth, ending the 205 year history of stock priced in eighths. As a consequence of this tick size reduction, liquidity was improved because both spreads and depths declined (Goldstein and Kavajecz (2000)).

I consider the year of 1997 as a year of liquidity shock and investigate the relationship between the change in stock liquidity from 1996 to 1998 and the change in firm innovation from the same period and from 1996 to 1999. The results in Panel B table 9 reports that the t-statistics of the coefficients of change in stock illiquidity captured by Amahud (2002) are from -2.48 to -1.66, implying that the change in liquidity is significantly positively correlated with change in firm innovation during this period of time.

Overall, the results in table 9 and 10 shows that the tick size reduction in 1997 and 2001 positively affects firm innovation. These results are consistent with the Dass et al.'s (2012) findings but inconsistent with Fang et al.'s (2013) results. These results are also supportive my hypothesis that stock market liquidity enhance firm innovation.

Table 9: Liquidity Shock and Firm Innovation

Panel A: Liquidity Shock around the Decimalization Year of 2001 and Firm Innovation

	$\Delta Lpatent_{i,t-1, t+1}$	$\Delta Lpatent_{i,t-1, t+1}$	$\Delta Lpcite_{i,t-1,t+1}$	$\Delta Lpcite_{i,t-1,t+1}$
$\Delta ILLIQ_{i,t-1, t+1}$	-0.001**		-0.002***	
	(-2.12)		(-3.25)	
$\Delta ZERO_{i,t-1,t+1}$		-0.211*		-0.438**
		(-1.83)		(-2.50)
$Lpatent_{i,t-1}$	-0.237***	-0.237***		
	(-15.61)	(-15.60)		
$Lpcite_{i,t-1}$			-0.397***	-0.397***
			(-15.82)	(-15.93)
$LSIZE_{i,t-1}$	0.054***	0.053***	0.094***	0.091***
	(4.50)	(4.45)	(5.73)	(5.74)
$\Delta LSIZE_{i,t-1}$	0.022*	0.017	0.008	-0.003
	(1.84)	(1.26)	(0.49)	(-0.16)
$\Delta LAT_{i,t-1}$	0.043	0.037	0.020	0.012
	(1.34)	(1.18)	(0.43)	(0.25)
$Totaldebt_{i,t-1}$	-0.068	-0.077	-0.138	-0.148
	(-1.17)	(-1.31)	(-1.45)	(-1.55)
$\Delta Totaldebt_{i,t-1}$	-0.099	-0.098	-0.193	-0.185
	(-1.17)	(-1.15)	(-1.46)	(-1.39)
$CAPX_{i,t-1}$	-0.005***	-0.005***	-0.009***	-0.009***
	(-3.25)	(-3.13)	(-6.89)	(-6.51)
$\Delta CAPX_{i,t-1}$	-0.005***	-0.005***	-0.009***	-0.009***
	(-3.23)	(-3.11)	(-6.83)	(-6.47)
$TANG_{i,t-1}$	-0.048	-0.050	-0.233**	-0.238**
	(-0.78)	(-0.82)	(-2.15)	(-2.23)
$\Delta TANG_{i,t-1}$	0.417***	0.415***	0.273	0.270
	(2.75)	(2.77)	(1.27)	(1.29)
$RDAT_{i,t-1}$	0.397*	0.411*	1.168*	1.194**
	(1.65)	(1.69)	(1.95)	(1.98)
$\Delta RDAT_{i,t-1}$	0.115	0.112	0.855**	0.851**
	(0.47)	(0.46)	(2.41)	(2.42)
_cons	-0.154***	-0.146***	-0.139*	-0.119
	(-4.10)	(-3.78)	(-1.66)	(-1.45)
N	3298	3305	3298	3305
R-square	0.1308	0.1314	0.1719	0.1723

Notes: This table reports the results from the regression model of change in firm innovation on change in stock liquidity and other control variables around the year of liquidity shock of 2001 and 1997. $\Delta Lpatent_{i,t-1,t+1}$ and $\Delta lpcite_{i,t-1,t+1}$ are respectively the change in the logarithm of number of patents of firm i, and the adjusted number of patent citations per patent of firm i from year t-1 to year t+1. $\Delta ILLIQ_{i,t-1}$ and $\Delta ZERO_{i,t-1,t+1}$ are the change in Amihud (2002) illiquidity and zero daily return measures. LSIZE, totaldebt, CAPX, TANG, and RDAT are respectively logarithm of market capitalization, total debt ratio, capital expenditure ratio, tangible assets ratio, and R&D expenditures to total assets. ***, **, and * denotes a rejection of the null hypothesis at the 1%, 5%, and 10% level, respectively. Panel A reports the effects of the change in liquidity around the decimalization year of 2001 on firm innovation and panel B shows the effects of the change in liquidity from 1996 to 1998 on the change in firm innovation.

Table 9: Liquidity Shock and Firm Innovation (continued)

Panel B: Liquidity Shock around the Tick Size Reduction Year of 1997 and Firm Innovation

	$\Delta Lpatent_{i,t-1, t+1}$	$\Delta Lpatent_{i,t-1, t+1}$	$\Delta Lpcite_{i,t-1,t+1}$	$\Delta Lpatent_{i,t-1, t+2}$	$\Delta Lpatent_{i,t-1, t+2}$	$\Delta Lpcite_{i,t-1,t+2}$
$\Delta ILLIQ_{i,t-1, t+1}$	-0.000**	-0.000*	-0.000*	-0.000**	-0.000*	-0.000**
	(-2.34)	(-1.81)	(-1.86)	(-2.01)	(-1.66)	(-2.48)
$Lpatent_{i,t-1}$	-0.231***	-0.285***		-0.303***		
	(-11.37)	(-17.98)		(-11.38)		
$Lpcite_{i,t-1}$			-0.497***		-0.497***	-0.430***
			(-23.94)		(-21.80)	(-19.85)
$LSIZE_{i,t-1}$		0.059***	0.110***		0.096***	
		(5.27)	(5.55)		(6.14)	
$\Delta LSIZE_{i,t-1}$	-0.029**	0.014*	0.058*	-0.026**	0.018	-0.067**
	(-2.52)	(1.76)	(1.99)	(-2.54)	(0.90)	(-2.43)
$\Delta LAT_{i,t-1}$	0.086***	0.104***	0.054	0.123***	0.145***	0.135***
	(2.78)	(3.55)	(1.41)	(3.75)	(3.30)	(2.69)
$Totaldebt_{i,t-1}$		0.048	-0.108		-0.020	
		(0.76)	(-1.03)		(-0.18)	
$\Delta Totaldebt_{i,t-1}$	-0.196***	-0.176**	-0.163	-0.262***	-0.372*	-0.392**
	(-2.80)	(-2.34)	(-1.67)	(-3.24)	(-1.70)	(-2.20)
$CAPX_{i,t-1}$		0.007	0.013		0.021	
		(0.90)	(0.89)		(1.29)	
$\Delta CAPX_{i,t-1}$	0.001***	0.001***	0.003***	0.001***	0.003***	0.003***
	(20.17)	(17.72)	(40.22)	(3.62)	(18.49)	(48.14)
$TANG_{i,t-1}$		0.008	0.023		0.027	
		(0.13)	(0.31)		(0.23)	
$\Delta TANG_{i,t-1}$	0.326**	0.284*	0.090	0.318**	0.219*	0.282**
	(2.21)	(1.96)	(0.46)	(2.42)	(1.80)	(2.35)
$RDAT_{i,t-1}$		0.172**	1.053***		0.868***	
		(2.23)	(4.27)		(3.56)	
$\Delta RDAT_{i,t-1}$	0.097	0.240*	0.976**	0.310**	1.345***	0.881***
	(0.66)	(1.70)	(2.17)	(2.22)	(5.07)	(4.35)
_cons	0.089***	-0.184***	-0.263**	0.101***	-0.215**	0.241***
	(7.31)	(-2.93)	(-2.39)	(6.01)	(-2.27)	(15.15)
N	3584	3584	3584	3584	3584	3584
R-square	0.1503	0.1755	0.2269	0.2200	0.2376	0.2078

1.3.3.5 Out–of –sample

Literature has documented several factors affecting firm's innovation activity, including capital, labor skill, market competition, macroeconomic condition, and legal system, etc. These variables have changed over time, causing a change in firm's innovation productivity.

In the previous section, I document that aggregate stock liquidity has predictive power for both the whole and subsample period. In this section, I examine the effects of aggregate liquidity on aggregate innovation out of sample. If the predictive power of aggregate liquidity is persistent, I expect it will hold in this period.

I choose the period of time from 1955 to 1975 when all relevant macroeconomic variables are available. More importantly, there are no official R&D expenditures before 1953. Before discussing the effects of aggregate liquidity on aggregate innovation, I briefly review the aggregate patent applications and macroeconomic conditions during this period. More details can be found in Griliches' (1980, 1989, and 1998).

This period witnessed two slowdowns in the growth of labor productivity: 1965-1973 and 1973-1978 (Griliches (1980)). The total number of patent applications increased significantly from 1955 to 1966, fluctuated and peaked in 1970, then declined until the mid of 1980s. Total R&D expenditures also significantly grew up before 1968 and then decreased until 1975. Although the decrease in patenting activity in late 1960s and 1970s may have been driven by the decline in R&D, it also was associated with some economic factors. First, there was a shift in patenting activity and R&D expenditures among industries. Some traditionally high-patenting industries such as chemicals, rubber or

fabricated metals reduced both R&D expenditures and patent applications, while computer and electrical equipment industries experienced high R&D expenditures but achieved less patent applications during this period. Second, the global economy went into a difficult stage. Third, spending from federal government on R&D was low. Finally, the patent grant process was slow; it took on average more than 2 years for a patent to be granted.

Due to the economic condition, the lag time between R&D investments and patenting should be longer during this period. I lengthen the lag between aggregate liquidity and innovation from 1 to 2.5 years. Using model (4) in the previous section, I investigate the effects of aggregate liquidity on future aggregate innovation growth rate. Because most stocks named in CRSP were traded in NYSE during this period, I consider both equally weighted and value weighted aggregate Amihud (2002) liquidity and aggregate zero daily return measures. The results are reported in table 10.

As discussed above, the slowdowns in patenting productivity may result in an increase in the lag between input and output of innovation. Consistent with this hypothesis, table 10 shows that aggregate liquidity is not correlated with aggregate innovation growth rate next year. However, it is significantly correlated with this rate in the next 2 years. The absolute values of t-statistics of coefficients of aggregate Amihud (2002) liquidity measures are greater than 3.4. T-statistic of coefficient of equally weighted aggregate zero daily return measure with is -1.94. The results are consistent when I choose the lag of 1.5 years or 2.5 years (not reported).

Table 10: Out– of – sample

	(1) $AgINNO_{t+24}$	(2) $AgINNO_{t+24}$	(3) $AgINNO_{t+24}$	(4) $AgINNO_{t+24}$	(5) $AgINNO_{t+12}$	(6) $AgINNO_{t+12}$	(7) $AgINNO_{t+12}$	(8) $AgINNO_{t+12}$
Intercept	0.014	0.012	0.009	0.005	0.021*	0.019	0.021*	0.022*
	(0.97)	(0.81)	(0.58)	(0.33)	(1.68)	(1.61)	(1.74)	(1.80)
$AgILLIQ1_t$	-0.634***				-0.014			
	(-3.49)				(-0.09)			
$AgILLIQ2_t$		-0.400***				0.092		
		(-3.43)				(0.83)		
$AgZERO1_t$			0.210				0.217	
			(0.42)				(0.56)	
$AgZERO2_t$				-1.104**				0.555
				(-1.94)				(1.18)
$AgINNO_t$	0.402***	0.408***	0.397***	0.393***	0.498***	0.495***	0.500***	0.497***
	(6.64)	(6.67)	(6.10)	(6.23)	(8.35)	(8.26)	(8.41)	(8.34)
$dGDP_t$	-0.740	-0.646	-0.990**	-0.947*	-0.738	-0.807	-0.724	-0.782
	(-1.48)	(-1.26)	(-1.98)	(-1.84)	(-1.34)	(-1.42)	(-1.34)	(-1.41)
$Term_t$	-0.002	0.003	0.008	0.010	-0.011	-0.009	-0.011	-0.011
	(-0.17)	(0.30)	(0.73)	(0.97)	(-1.17)	(-1.040	(-1.25)	(-1.29)
$Cdefault_t$	-0.027	-0.054	-0.103	-0.083	-0.009	-0.013	-0.013	-0.017
	(-0.23)	(-0.46)	(-0.83)	(-0.69)	(-0.09)	(-0.13)	(-0.13)	(-0.17)
N	240	240	240	240	240	240	240	240
R-square	0.2169	0.2120	0.1673	0.1814	0.2532	0.2558	0.2538	0.257

Notes: This table reports the results from the regression models of aggregate innovation on aggregate liquidity measure and other macro variables last 12 or 24 months for the period 1955 to 1975. $AgINNO_{t+12\ (24)}$ is aggregate innovation captured by the number of patent applications next year (next two years). $AgILLIQ1_t$ and $AgILLIQ2_t$ are respectively the aggregate value weighted and equally weighted Amihud (2002) illiquidity measure. $AgZERO1_t$ and $AgZERO2_t$ are respectively the aggregate value weighted and equally weighted zero daily return measures at month t. $dGDP_t$, $Term_t$, $Cdefault_t$ and are respectively the change in GDP growth rate, term structure, and the change in default spread. ***, **, and * denotes a rejection of the null hypothesis at the 1%, 5%, and 10% level, respectively.

An interesting result in this table is that the change in real GDP growth rate is negatively correlated with future aggregate innovation, which is opposite to the results in the previous section. However, consistent with previous results, both term structure and default spread do not play any important role in explaining future aggregate innovation.

Overall, while both term structure and default spread are not significantly correlated with future aggregate innovation, the relation between change in GDP growth rate and future aggregate innovation seems to be mixed. In contrast, the effects of aggregate liquidity on future aggregate innovation tend to be persistent. These results suggest the predictive power of aggregate liquidity on future innovation.

1.4 Aggregate Liquidity, External Finance, and Aggregate Innovation

1.4.1 Aggregate Liquidity and External Finance

In the previous section, I document that stock market liquidity encourages innovation at the aggregate level. In this section, I investigate the underlying reasoning for this positive relationship. I hypothesize that cash flow and the availability of external capital are important determinants in the relationship between stock market liquidity and innovation. When the stock market becomes more liquid, firms easily raise external capital at lower costs to finance their innovation activities. This effect is more pronounced for small firms or firms with less cash flow.

I first re-examine the effects of aggregate liquidity on a firm's external finance. Butler et al. (2005) find that stock liquidity is an important determinant of the cost of raising external capital because both flotation costs and investment bank fees are lower when stock liquidity improves. I go a step further by investigating the effects of aggregate

liquidity on equity and debt issuances in the period from 1975 to 2005. Specifically, I use the follow regression:

$$EFIN_{i,t} = \alpha + \beta_1 AILLIQ_t + \gamma X_{i,t-1} + \mu_i + \eta_t + \varepsilon_{i,t} \quad (6)$$

Where $EFIN_{i,t}$ is external finance captured by equity and debt issuances of firm i in year t, $AILLIQ_t$ is aggregate Amihud (2002) liquidity ($AgILLIQ_t$) or zero daily return measures ($AgZERO_t$) in year t , $X_{i,t-1}$ is a vector of firm and industry characteristics which include Tobin's Q, size, total debt ratio, return on assets, capital expenditures, tangibility, age, R&D to total assets, firm stock liquidity, cash, and Herfindahl index. The definitions of these variables are detailed in the appendix. μ_i is firm fixed effects and η_t is time fixed effects.

I focus on external financing at the firm level because I want to examine both the effects of aggregate stock liquidity and firm's characteristics on firm equity and debt issuances. The results from this model (6) are reported in table 11.

Table 11 indicates that two aggregate liquidity measures significantly affect both equity and debt issuances. The absolute values of t-statistics of the coefficients for equity financing are greater than 9.36, while these values for debt financing are greater than 3.64. Obviously, table 11 shows that the effects of aggregate liquidity are more pronounced on equity issuance. Consistently, firm stock liquidity are significantly correlated with equity and debt issuances and the relationship between firm stock liquidity and equity financing is much stronger than the relationship between firm stock liquidity and debt financing.

Table 11: Debt and Equity Issuance

	(1) $ISSEQUITY_{i,t}$	(2) $ISSEQUITY_{i,t}$	(3) $ISSDEBT_{i,t}$	(4) $ISSDEBT_{i,t}$
$ILLIQ_{i,t}$	-0.010***		-0.001**	
	(-10.02)		(-2.21)	
$ZERO_{i,t}$		-0.469***		-0.077***
		(-19.88)		(-5.15)
$AgILLIQ_t$	-0.133***		-0.056***	
	(-9.36)		(-5.06)	
$AgZERO_t$		-0.133***		-0.050***
		(-6.82)		(-3.64)
$Q_{i,t-1}$	0.060***	0.059***	0.006***	0.006***
	(6.59)	(6.50)	(4.82)	(4.72)
$LSIZE_{i,t-1}$	-0.058***	-0.066***	-0.002	-0.004*
	(-8.15)	(-9.36)	(-1.15)	(-1.83)
$Totaldebt_{i,t-1}$	0.045**	0.049**	-0.397***	-0.397***
	(2.33)	(2.52)	(-22.93)	(-22.85)
$ROA_{i,t-1}$	-0.260***	-0.286***	0.019	0.015
	(-5.59)	(-6.16)	(1.10)	(0.85)
$CAPX_{i,t-1}$	-0.000	-0.000	-0.000***	-0.000***
	(-1.00)	(-1.01)	(-3.77)	(-3.72)
$TANG_{i,t-1}$	0.023	0.026	0.074***	0.074***
	(0.98)	(1.11)	(3.94)	(3.97)
$LAGE_{i,t-1}$	-0.049***	-0.060***	-0.040***	-0.042***
	(-4.46)	(-5.47)	(-6.59)	(-6.88)
$RDAT_{i,t-1}$	1.093***	1.071***	0.073	0.069
	(7.26)	(7.18)	(1.57)	(1.48)
$CASH_{i,t-1}$	-0.155***	-0.155***	-0.074***	-0.074***
	(-5.52)	(-5.53)	(-4.77)	(-4.78)
$HHI_{i,t-1}$	0.018	0.016	0.000	-0.000
	(1.28)	(1.14)	(0.03)	(-0.01)
_cons	0.359***	0.457***	0.198***	0.201***
	(12.55)	(15.90)	(9.56)	(10.74)
N	60,034	60,034	60,034	60,034
R^2	0.1704	0.1743	0.0056	0.0059

Notes: This table reports the results from the regression model of external financing on aggregate liquidity and other control variables for the period from 1975 to 2005. $ISSEQUITY_{i,t}$ and $ISSDEBT_{i,t}$ is the equity and debt issuances for firm i in year t, respectively. $ILLIQ_{i,t}$ and $ZERO_{i,t}$ are the Amihud (2002) illiquidity and zero daily return measures for firm i in year t. $AgILLIQ_t$ and $AgZERO_t$ are respectively the aggregate Amihud (2002) illiquidity and zero daily return measures in year t. Q, LSIZE, totaldebt, ROA, CAPX, TANG, RDAT, and CASH are respectively Tobin's Q, logarithm of market capitalization, total debt ratio, return on assets, capital expenditure ratio, tangible assets ratio, R&D expenditures to total assets, and cash holding ratio. HHI is the Herfindahl index, and LAGE is logarithm of one plus firm age. ***, **, and * denotes a rejection of the null hypothesis at the 1%, 5%, and 10% level, respectively.

The results from table 11 also show that young firms or firms with high Tobin'Q or less cash holding tend to issue both more equity and debt. Firms with less capital expenditures or high tangible assets tend to issue more debt than equity. In contrast, small firms or firms with high R&D to total assets or less return on assets tend to raise more external equity than debt.

The relationship between firm size and external financing is very straightforward. The literature documents that small firms are riskier and have less tangible assets, so they find it difficult to raise debt. As a result, they prefer to issue more equity to finance their activities. This external financing strategy is more pronounced when the stock market is in healthy. Similarly, the relationship between innovation and external financing is widely documented in the recent literature. Hall et al. (2009) and Brown et al. (2009) show that the U.S. small firms mainly finance their innovation with equity and cash flow. Moreover, Atanassov et al. (2007) show that banks are reluctant to finance R&D projects because their outcomes very uncertain. Thus, R&D investments heavily depend on external capital resources from the stock markets. Consistent with this statement, the results in table 11 show that firms with high R&D investments usually issue more external equity rather than debt.

1.4.2 Firm Characteristics and External Financing

The role of external equity financing in encouraging R&D investments is widely documented in the recent literature. Brown et al. (2009) argue that young firms tend to finance their R&D by cash flow and external equity. Atanassov et al. (2007) document that U.S. public firms that create novel innovations rely more on external equity and

public debt. Hall et al. (2009) survey the current literature on financing R&D and indicate that equity is the main financial sources for R&D.

From the evidence that cash flow and equity are important determinants of a firm's R&D investments and the evidence in table 11 that small firms tend to issue more external financing, I hypothesize that the effects of stock market liquidity on external equity issuance is more pronounced for small firms. To test this hypothesis, every year I divide all firms into two groups based on their size. I then use the model (6) to regress the debt and equity issuances for firms in each group. The results from this regression model are reported in table 12 (panel A).

Panel A of table 12 shows that when stock markets become more liquid, small firms only issue more equity but large firms issue both equity and debt. Furthermore, the coefficient of aggregate illiquidity for small firms is -0.188 while this figure for large firms is only -0.073. This implies that when aggregate stock market liquidity improves by one standard deviation (0.072), small firms on average will increase their equity issuance by 1.35% whereas this figure for large firms is only 0.5%. This evidence supports the statement that small firms rely more on stock markets to raise external capital.

Panel A of table 12 also presents that firm stock liquidity is an important determinant of equity issuance for both small and large firms. However, in contrast to the effects of aggregate stock market liquidity on equity issuance, the coefficient of firm stock liquidity for small firms is -0.008 while this figure for large firms is -0.037. Moreover, firm stock liquidity only affects debt issuance for large firms.

Table 12: Debt and Equity Issuance and Firm Characteristics

	Panel A: Firm size				Panel B: R&D investments			
	Small firms		Large firms		Firms with R&D		Firms without R&D	
	$ISSEQUITY_{i,t}$	$ISSDEBT_{i,t}$	$ISSEQUITY_{i,t}$	$ISSDEBT_{i,t}$	$ISSEQUITY_{i,}$	$ISSDEBT_{i,t}$	$ISSEQUITY_{i,}$	$ISSDEBT_{i,t}$
$ILLIQ_{i,t}$	-0.008***	-0.000	-0.037***	-0.020***	-0.014***	-0.000	-0.006***	-0.002**
	(-8.15)	(-0.78)	(-4.43)	(-3.13)	(-9.54)	(-0.27)	(-7.11)	(-2.06)
$AgILLIQ_{t}$	-0.188***	-0.010	-0.073***	-0.056***	-0.175***	-0.027**	-0.099***	-0.071***
	(-7.56)	(-0.57)	(-6.71)	(-5.29)	(-7.34)	(-2.24)	(-6.12)	(-4.81)
$Q_{i,t-1}$	0.127***	0.008***	0.028***	0.006***	0.061***	0.005***	0.056***	0.014***
	(6.92)	(3.31)	(4.43)	(3.47)	(5.65)	(3.67)	(6.68)	(4.27)
$LSIZE_{i,t-1}$	-0.097***	0.004	-0.036***	-0.008***	-0.072***	0.002	-0.046***	-0.007**
	(-7.44)	(1.18)	(-7.51)	(-2.83)	(-6.26)	(0.79)	(-7.53)	(-2.14)
$Totaldebt_{i,t-1}$	0.126***	-0.483***	0.041**	-0.374***	0.085***	-0.376***	0.025	-0.427***
	(5.12)	(-15.47)	(2.29)	(-19.39)	(3.04)	(-20.79)	(0.84)	(-14.66)
$ROA_{i,t-1}$	-0.140**	0.003	-0.168***	0.055**	-0.279***	0.020	-0.160***	-0.008
	(-2.29)	(0.14)	(-3.03)	(2.26)	(-4.26)	(1.02)	(-2.73)	(-0.22)
$CAPX_{i,t-1}$	0.000***	-0.000**	-0.000**	-0.000***	0.000	-0.000	-0.000**	-0.000***
	(2.86)	(-2.17)	(-2.30)	(-6.49)	(0.64)	(-1.45)	(-2.31)	(-8.51)
$TANG_{i,t-1}$	0.006	0.108***	-0.004	0.057**	-0.036	0.059***	0.044	0.081***
	(0.21)	(3.80)	(-0.23)	(2.31)	(-0.97)	(2.72)	(1.40)	(3.01)
$LAGE_{i,t-1}$	-0.020	-0.024**	-0.059***	-0.030***	-0.068***	-0.021**	-0.033***	-0.050***
	(-1.16)	(-2.54)	(-5.73)	(-3.63)	(-3.82)	(-2.50)	(-4.23)	(-5.66)
$RDAT_{i,t-1}$	1.037***	0.107*	0.804***	0.081	1.095***	0.098**	.	.
	(5.13)	(1.77)	(3.70)	(1.49)	(6.94)	(2.05)	.	.
$CASH_{i,t-1}$	-0.144***	-0.083***	-0.064***	-0.081***	-0.168***	-0.083***	-0.168***	-0.078**
	(-3.83)	(-3.59)	(-2.67)	(-3.96)	(-5.23)	(-5.18)	(-3.08)	(-2.34)
$HHI_{i,t-1}$	0.006	0.004	0.006	-0.002	0.037	0.009	-0.009	0.003
	(0.26)	(0.25)	(0.51)	(-0.13)	(1.41)	(0.59)	(-0.75)	(0.23)
N	29,998	29,998	29,978	29,978	29,745	29,745	30,231	30,231
R^2	0.2126	0.0038	0.1302	0.0068	0.1911	0.0103	0.0547	0.0065

Notes: This table presents the results from the regression model of external financing on aggregate liquidity and other control variables for the period from 1975 to 2005. $ISSEQUITY_{i,t}$ and $ISSDEBT_{i,t}$ is the equity and debt issuances for firm i in year t, respectively. $ILLIQ_{i,t}$ and $ZERO_{i,t}$ are the Amihud (2002) illiquidity and zero daily return measures for firm i in year t. $AgILLIQ_{t}$ and $AgZERO_{t}$ are respectively the aggregate Amihud (2002) illiquidity and zero daily return measures in year t. Q, LSIZE, totaldebt, ROA, CAPX, TANG, RDAT, and CASH are respectively Tobin's Q, logarithm of market capitalization, total debt ratio, return on assets, capital expenditure ratio, tangible assets ratio, R&D expenditures to total assets, and cash holding ratio. HHI is the Herfindahl index, and LAGE is logarithm of one plus firm age. ***, **, and * denotes a rejection of the null hypothesis at the 1%, 5%, and 10% level, respectively.

As documented in Hall et al. (2009), the firms in the U.S. tend to finance their innovation projects by cash flow or equity. Thus, I expect that the effects of stock market liquidity on external financing are stronger for innovative firms. To test this prediction, I divide all firms into two groups: the groups of firms with and without R&D investments. I then use model (5) to examine the sensitivity of a firm's financing to the stock market liquidity. The results are shown in panel B of table 12.

The results in table 12 present that aggregate stock market liquidity only affects innovative firms' decisions to issue more equity. In contrast, firms without R&D investments issue both debt and equity when stock markets become more liquid. However, the coefficient of aggregate stock market liquidity for innovative firms is -0.175, which nearly doubles this figure for firms without R&D investments. This evidence suggests that stock market liquidity is an important determinant of raising external finance for innovative firms.

1.4.3 Financing, Firm Size and R&D Investments

The previous section shows that small firms tend to raise more equity than the large ones. Moreover, the current literature documents that small firms are riskier and tend to finance their R&D activities by cash holding and equity. This implies that small firms tend to be more sensitive to the stock market condition to finance their R&D than large firms. As a result, the effects of stock market liquidity on R&D are more pronounced for small firms.

To test this hypothesis, every year I divide all these firms into two groups based on their size. I then aggregate all R&D expenditures for each group. Because aggregate R&D expenditures are non-stationary, I detrend them by taking the difference in their values (in

logs). I investigate the effects of aggregate liquidity on aggregate R&D expenditures by running the regression model in section 1.3.1 (model 4).

Table 13: Firm Size and Aggregate R&D Expenditures

	Small		Big	
	(1)	(2)	(3)	(4)
Model	$AgRD1_t$	$AgRD1_t$	$AgRD2_t$	$AgRD2_t$
Intercept	0.085	0.079	0.064	0.070
	(1.55)	(1.40)	(1.34)	(1.58)
$AgILLIQ_t$	-0.232**		-0.026	
	(-2.24)		(-0.64)	
$AgZERO_t$		-0.223*		0.059
		(-2.09)		(1.63)
$AgRD1_{t-1}$	0.121	-0.197		
	(0.59)	(-0.95)		
$AgRD2_{t-1}$			0.310	0.346
			(0.98)	(1.27)
$dGDP_{t-1}$	4.932	3.755	3.396**	2.767**
	(1.40)	(1.03)	(2.51)	(2.08)
$term_{t-1}$	-0.013	0.016	0.000	-0.002
	(-0.52)	(0.66)	(0.01)	(-0.19)
$Cdefault_{t-1}$	-0.081	-0.040	0.038	0.034
	(-0.96)	(-0.45)	(1.27)	(1.32)
N	31	31	31	31
R-square	0.1958	0.1352	0.1797	0.2188

Notes: This table summarizes the results from the regression models of aggregate R&D expenditures for groups of firms with different size on aggregate liquidity measure and other macro variables in the period 1976 to 2006. Every year, I divide all these firms into two groups based on their size. I then calculate the detrended aggregate patent for each group. $AgRD1(2)_t$ is aggregate R&D expenditures for firms in group 1 (2) in year t. $AgILLIQ_t$ and $AgZERO_t$ are respectively the aggregate Amihud (2002) illiquidity and zero daily return measures in year t. $dGDP_t$, $Term_t$, $Cdefault_t$ and are respectively the change in GDP growth rate, term structure, and the change in default spread. The Newey-West corrected t-statistics are reported in the parentheses. ***, **, and * denotes a rejection of the null hypothesis at the 1%, 5%, and 10% level, respectively.

Table 13 summarizes the results from this regression model. These results show that aggregate stock market liquidity is significantly correlated with aggregate R&D expenditures for small firms. The absolute values of t-statistics of these coefficients are

greater than 2.09. In contrast, both aggregate liquidity measures are insignificantly related to aggregate R&D expenditures for large firms. This evidence indicates that large firms do not rely on equity markets to finance their R&D investments.

1.4.4 Aggregate Liquidity and Equity Issuance Frequency

In this section, I robustly check the effects of aggregate liquidity on innovation through financing mechanisms by focusing on the relationship between aggregate liquidity and the average frequency of an innovative firm raising equity. I define an innovative firm as a firm invests in R&D one year around the year it issues equity. As shown in section 1.3.3.2, I simply classify all firms into two groups: high tech and non-high tech ones. Every year, I record the number of innovative firms issuing equity to total number of firms in each group and examine whether the effects of aggregate liquidity on this ratio is stronger for high tech industries. As expected, my results (not reported) show that the relationship between aggregate liquidity and the ratio of innovative firms issuing equity is more pronounced for firms in high tech industries.

1.5 Aggregate Liquidity, Size, and Mergers and Acquisitions

1.5.1 Aggregate Liquidity, Innovation, and Mergers and Acquisitions

In addition to the cost of raising external capital, merger and acquisition activities are hypothesized to drive the effects of aggregate stock market liquidity on innovation. In this section, I investigate the second mechanism that is the effect of aggregate liquidity on merger and acquisition activity. Specifically, I combine two strands of literature: the relation between aggregate liquidity and merger and acquisition as well as the relation

between innovation and merger and acquisition. I hypothesize that an increase in stock market liquidity will enhance merger and acquisition with innovation.

The first strand of literature suggests that the aggregate liquidity level tends to cause industry merger waves. Using the spread between the average rates charged for commercial and industrial loans and the fed funds rate to proxy for macro liquidity level, Harford (2005) shows that this capital liquidity plays an important role in explaining the aggregate merger waves. He finds that the merger activities tend to increase with the availability of capital in the markets. Consistently, Xu and Zhao (2009) use the aggregate liquidity measures under the framework of Holmström and Tirole (2001) which combines both aggregate corporate asset liquidity and market asset liquidity and find that higher aggregate liquidity is followed by more merger activity in the next period.

Literature on the relation between innovation and merger and acquisition suggests that more innovative companies tend to be acquirers while less innovative companies are more likely to be acquired (Zhao (2009), and Bena and Li (2013)). Moreover, Zhao (2009) documents that among the bidders, the relatively more innovative ones are less likely to complete a deal and less innovative bidders benefit more from acquisitions. She concludes that acquisitions help firms' innovation efforts.

I focus on merger and acquisition activities with innovation. My merger and acquisition data is largely based on Bena and Li (2013). As shown in figure 2, the number of targets with patent tends to be high following the high level of aggregate liquidity. This pattern is persistent for the number of acquirers or the number of deals with patents.

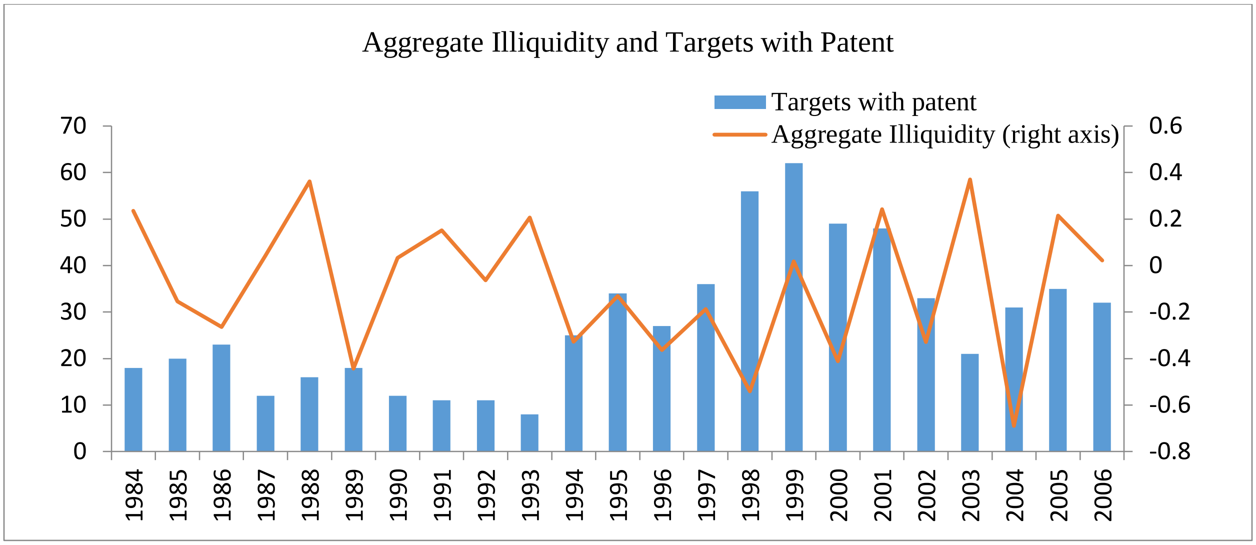

Figure 2: Stock Market Illiquidity and Targets with Patent

Notes: This figure shows time-series plots of number of targets with patent and the aggregate Amihud (2002) illiquidity measure (AgLIQ). The gray bars are the number of all targets with patent in a year (the left axis). The line is the detrended AgLIQ (the right axis) which is the change in this illiquidity measure (in logs). Amihud (2002) illiquidity measure is first calculated for each firm for each year. Then the value –weighted cross-sectional average for each year is calculated. More precise definition is in section II.C. Note that AgLIQ reflects illiquidity, so a high value means that stock markets are illiquid.

I check this positive relation by running the regression model of aggregate targets with patents or total number of deals with patent on aggregate liquidity and other macro variables which are mentioned in section 1.3.1. I scale targets with patent by total targets in the same year and total number of deals with patent by the total number of deals in the same year. I use the same framework as shown in section 1.3.1 to deal with non-stationary time series. I then run the regression model of ratios of targets with patent and deals with patent on aggregate liquidity and other macro-variables as mentioned in section 1.3.1. The results from this regression are summarized in table 14.

Table 14: Aggregate Liquidity and Aggregate Mergers and Acquisitions

	Target with patent rate				All deal with patent rate			
	$Targetrate_{t+2}$	$Targetrate_{t+2}$	$Targetrate_{t+2}$	$Targetrate_{t+1}$	$Dealrate_{t+2}$	$Dealrate_{t+2}$	$Dealrate_{t+2}$	$Dealrate_{t+1}$
Intercept	-0.054	-0.037	-0.035	0.028	-0.023	-0.020	-0.036	-0.005
	(-0.72)	-0.6	(-0.42)	(0.36)	(-0.58)	(-0.48)	(-0.74)	(-0.15)
$AgILLIQ_t$	-0.603***	-0.576**			-0.251*	-0.229		
	(-2.83)	(-2.76)			(-1.85)	(-1.36)		
$AgZERO_t$			-0.489	0.067			-0.318*	-0.205*
			(-2.16)**	(0.25)			(-1.75)	(-1.84)
$Targetrate_t$	-0.472*	-0.512*	-0.236	-0.499***				
	(-1.81)	(-1.78)	(-1.09)	(-3.21)				
$Dealrate_t$					-0.280	-0.308	-0.229	-0.480***
					(-1.53)	(-1.36)	(-0.90)	(-2.23)
$dGDP_t$		30.676	44.094**			13.149*	21.384***	
		(1.59)	(2.17)			(2.00)	(2.87)	
$Cterm_t$		-0.030	-0.102			-0.018	-0.057	
		(-0.42)	(-1.25)			(-0.38)	(-1.38)	
$Cdefault_t$		0.104	-0.114			-0.136	-0.331	
		(0.31)	(-0.24)			(-0.7)	(-1.62)	
N	21	21	21	21	21	21	21	21
R-square	0.2519	0.3979	0.3176	0.2497	0.2006	0.3310	0.3632	0.2877

Notes: This table shows the effects of aggregate liquidity on merger and acquisition in the period from 1984 to 2006. $Targetrate_{t+2(1)}$ is the ratio of number of targets with patent to total number of targets next two (one) years. $Dealrate_{t+2(1)}$ is the ratio of number of deal with patent to total number of deals next two (one) years. $AgILLIQ_t$ and $AgZERO_t$ are respectively the aggregate Amihud (2002) illiquidity and zero daily return measures in year t. $dGDP_t$, $Cterm_t$, $Cdefault_t$ and are respectively the change in GDP growth rate, the change in term structure, and the change in default spread. The Newey-West corrected t-statistics are reported in the parentheses. ***, **, and * denotes a rejection of the null hypothesis at the 1%, 5%, and 10% level, respectively.

These results show that the aggregate liquidity is significantly positively correlated with both aggregate number of targets with patent and aggregate number of deals with patent, but the effects of aggregate liquidity on aggregate number of targets with patent are stronger[14]. This evidence shows that aggregate liquidity is an important determinant of merger and acquisition activities with patents.

1.5.2 Merger and Acquisition, Firm Size, and Innovation

Using the ratio of R&D expenditures to size to capture innovation, the current literature documents that small firms are more innovative. Cremers et al. (2009) find that small firms tend to be acquired by large firms. Moreover, Phillips and Zhdanov (2012) develop a model and provide empirical evidence to show that large firms optimally decide to purchase small innovative firms and conduct less R&D than small ones. However, using patenting activity, large firms have more patent counts and higher citations per patent. This evidence indicates that merger and acquisition activity is an important channel for firms to generate innovation: large firms acquire innovation from small firms and small firms benefit from this deal. This result indicates that large firms play different roles in patenting activity.

Table 15 shows the effects of aggregate liquidity on aggregate patent for both small and large firms. As discussed in the previous section, I just focus on the firms with patents. Every year, I divide all these firms into two groups based on their market capitalization in the previous two years. I allow a two year gap to make sure that firms have time to raise

[14] In addition to the significantly positive relations between aggregate stock market liquidity and merger and acquisition activities with patents, I document that, consistent with Xu and Zhao (2009), aggregate stock liquidity is positively correlated with aggregate number of targets or deals. However, this effect is weaker than the effects of aggregate stock liquidity on deals or targets involving patents.

external capital to finance their innovation activity and that large firms can acquire small firms if they have a plan to do so.

Table 15: Firm Size and Aggregate Number of Patents

	Small		Big	
	(1)	(2)	(3)	(4)
	$AgINNO_{t+12}$	$AgINNO_{t+12}$	$AgINNO_{t+12}$	$AgINNO_{t+12}$
Intercept	0.001	0.006	0.013	0.011
	(0.09)	(0.47)	(1.43)	(1.14)
$AgILLIQ_t$	-0.195*		-0.165***	
	(-1.82)		(-2.83)	
$AgZERO_t$		0.140		-0.384**
		(0.5)		(-1.93)
$AgINNO1_t$	0.084*	0.078		
	(1.64)	(1.50)		
$AgINNO2_t$			0.610***	0.609***
			(7.46)	(7.50)
$dGDP_t$	1.850*	1.907*	1.863***	1.797***
	(1.87)	(1.90)	(2.90)	(2.77)
$term_t$	0.002	0.000	-0.007	-0.006
	(0.27)	(0.04)	(-1.53)	(-1.28)
$Cdefault_t$	-0.040	-0.050	-0.056	-0.061
	(-0.55)	(-0.68)	(-1.16)	(-1.28)
N	372	372	372	372
Adj R-square	0.0101	0.0042	0.3639	0.3624

Notes: This table reports the results from the regression models of aggregate innovation for groups of firms with different size on aggregate liquidity measure and other macro variables during the prior 12 months in the period 1976 to 2006. Every year, I divide all these firms into two groups based on their size in two previous years. I then calculate the detrended aggregate patent for each group. $AgINNO1(2)_{t+12}$ is aggregate number of patent applications for firms in group 1 (2) next year (12 months). $AgILLIQ_t$ and $AgZERO_t$ are respectively the aggregate Amihud (2002) illiquidity and zero daily return measures at month t. $dGDP_t$, $Term_t$, $Cdefault_t$ and are respectively the change in GDP growth rate, term structure, and the change in default spread. The Newey-West corrected t-statistics are reported in the parentheses. ***, **, and * denotes a rejection of the null hypothesis at the 1%, 5%, and 10% level, respectively.

The results in table 15 show that these effects are stronger for large firms than for small ones. The value of t-statistic of aggregate Amihud (2002) liquidity measure is -2.83, and of aggregate zero daily return is -1.93. This evidence indicates that large firm innovation

captured by patenting activity is more sensitive to aggregate liquidity. This finding is also consistent with the theory of merger and acquisition in innovation, showing that small firms tend to invest more in R&D but large firms tend to acquire small innovative firms.

1.5.3 Aggregate Liquidity and Merger and Acquisition Frequency

I robustly check the relationship between aggregate liquidity and merger and acquisition with innovation by examining the effects of aggregate liquidity on the propensity of an innovative firm being an acquisition target. To simplify my analysis, I compute the ratios of number of targets to total number of firms in two groups: high tech and non-high tech. I then investigate the effects of aggregate liquidity on these ratios. My results (not reported) show that this effect is stronger for firms in high tech industries.

1.6 Aggregate Liquidity and Firm Innovation

In the previous sections, I mainly focus on the effects of aggregate liquidity on aggregate innovation. In this section, I robustly check the effects of aggregate liquidity on innovation at firm level. I use the most common patent database, the NBER patent database, from 1976 to 2002 to calculate several proxies for firm innovation: the log of number of patents scaled by size, the number of patents, the adjusted number of patent citations per patent scaled by size, as well as the adjusted number of patent citations per patent, and the ratio of R&D expenditures to total assets. These variables are widely used in the current literature (e.g. Hall et al. (2005), and Atanassov et al. (2007)).

To investigate the effects of aggregate liquidity on firm innovation, I run the regression of firm innovation proxies on aggregate liquidity measures and other control variables in the previous year. Specifically, I use the follow regression:

$$INNO_{i,t+1} = \alpha + \beta_1 AILLIQ_t + \gamma X_{i,t} + \mu_i + \eta_{t+1} + \varepsilon_{i,t+1} \quad (7)$$

where $INNO_{i,t+1}$ is a firm innovation proxy which can be the log of number of patents scaled by size, the number of patents, the adjusted number of patent citations per patent scaled by size, or the adjusted number of patent citations per patent of firm 1 at year t +1. $AILLIQ_t$ is aggregate Amihud (2002) liquidity ($AgILLIQ_t$) or zero daily return measures ($AgZERQ_t$) in year t, $X_{i,t}$ is a vector of firm and industry characteristics which include lag innovation proxies, Tobin's Q, size, total debt ratio, return on assets, capital expenditures, tangibility, age, R&D to total assets, firm stock liquidity, cash, KZ-index and Herfindahl index. The definitions of these variables are detailed in the appendix. μ_i is firm fixed effects and η_t is time fixed effects.

Table 16 summarizes the results from this regression model. These results show that both aggregate liquidity measures are significantly correlated with all firm innovation proxies. The absolute values of t-statistics of these coefficients in the models with time fixed effects are greater than 3.10. The absolute values of t-statistics of these coefficients in the models without time fixed effects are greater than 2.12. This evidence indicates that aggregate liquidity is an important determinant of firm innovation.

I also use ratio of R&D expenditures to total assets to measure firm innovation. Because R&D expenditures are inputs of a firm innovation process, I run the regression model (6) of R&D expenditure ratio on contemporaneous liquidity measures and other firm characteristics from the previous year. Consistently, aggregate liquidity measured by aggregate Amihud (2002) liquidity and aggregate zero daily returns are significantly positively correlated with firm innovation captured by R&D expenditures to total assets (table 17).

Table 16: Market Stock Liquidity and Firm Innovation

	(1) $Lpatents_{i,t+1}$	(2) $Lpatent_{i,t+1}$	(3) $Lpatent_{i,t+1}$	(4) $Lpatent_{i,t+1}$	(5) $clpatent_{i,t+1}$	(6) $Lpcite_{i,t+1}$	(7) $Lpcite_{i,t+1}$
$ILLIQ_{i,t}$	0.000***	0.003*	0.003*	0.000	0.000	-0.005*	-0.005*
	(2.86)	(1.72)	(1.72)	(0.30)	(0.30)	(-1.89)	(-1.94)
$AgILLIQ_{t}$			-0.470***		-0.250***		-1.610***
			(-5.57)		(-4.14)		(-11.86)
$Lpatent_{i,t}$				0.421***	-0.579***		
				(23.61)	(-32.53)		
$Lpcite_{i,t}$							0.126***
							(13.54)
$Q_{i,t}$	-0.000*	-0.010***	-0.010***	-0.006**	-0.006**	-0.010**	-0.009**
	(-1.80)	(-2.79)	(-2.79)	(-2.14)	(-2.14)	(-2.39)	(-2.24)
$LSIZE_{i,t}$	-0.002***	0.104***	0.104***	0.060***	0.060***	0.031***	0.026***
	(-8.72)	(9.05)	(9.05)	(8.17)	(8.17)	(2.97)	(2.77)
$Totaldebt_{i,t}$	-0.001	0.041	0.041	0.014	0.014	-0.005	-0.006
	(-0.56)	(0.94)	(0.94)	(0.49)	(0.49)	(-0.11)	(-0.14)
$ROA_{i,t}$	-0.003***	-0.046	-0.046	0.005	0.005	-0.001	-0.002
	(-3.26)	(-0.89)	(-0.89)	(0.12)	(0.12)	(-0.01)	(-0.03)
$CAPX_{i,t}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.42)	(1.01)	(1.01)	(1.07)	(1.07)	(0.70)	(0.65)
$TANG_{i,t}$	-0.002	0.177**	0.177**	0.086*	0.086*	0.224***	0.198***
	(-1.18)	(2.51)	(2.51)	(1.93)	(1.93)	(3.37)	(3.29)
$LAGE_{i,t}$	-0.000	0.132***	0.132***	0.057**	0.057**	0.129***	0.101***
	(-0.35)	(3.37)	(3.37)	(2.35)	(2.35)	(3.87)	(3.40)
$RDAT_{i,t}$	0.001	0.474***	0.474***	0.226**	0.226**	0.485***	0.398***
	(0.54)	(4.18)	(4.18)	(2.46)	(2.46)	(2.93)	(2.60)

Table 16: Market Stock Liquidity and Firm Innovation (continued)

	(1) $Lpatents_{i,t+1}$	(2) $Lpatent_{i,t+1}$	(3) $Lpatent_{i,t+1}$	(4) $Lpatent_{i,t+1}$	(5) $clpatent_{i,t+1}$	(6) $Lpcite_{i,t+1}$	(7) $Lpcite_{i,t+1}$
$CASH_{i,t}$	-0.001	0.076	0.076	0.033	0.033	0.202***	0.174***
	(-1.25)	(1.46)	(1.46)	(0.88)	(0.88)	(3.26)	(3.05)
$HHI_{i,t}$	-0.000	-0.020	-0.020	-0.009	-0.009	0.087	0.074
	(-0.55)	(-0.26)	(-0.26)	(-0.19)	(-0.19)	(1.25)	(1.18)
$Kzindex_{i,t}$	-0.000	0.000***	0.000***	0.000***	0.000***	0.000	0.000
	(-1.49)	(2.71)	(2.71)	(2.58)	(2.58)	(1.53)	(1.56)
_cons	0.020***	-0.159	-0.245**	-0.044	-0.090	0.186**	-0.101
	(14.57)	(-1.62)	(-2.33)	(-0.71)	(-1.37)	(2.17)	(-1.08)
Method	F, T, OLS	F, T, OLS	F, T, OLS	F, T, OLS	F, T, OLS	F, T, OLS	F, T, OLS
N	55,375	55,375	55,375	55,375	55,375	55,375	55,375
R^2	0.0625	0.1677	0.1677	0.7345	0.0731	0.0531	0.2776

Notes: This table reports the results from the regression model of firm innovation on aggregate liquidity and other control variables for the period 1976 to 2002. $Lpatents_{i,t+1}$ is the logarithm of number of patents scaled by size of firm i in year t+1, $lpatent_{i,t+1}$, $clpatent_{i,t+1}$ and $lpcite_{i,t+1}$ are respectively the logarithm of the number of patents, the change in the logarithm of the number of patents, and the adjusted number of patent citations per patent of firm i at year t +1. $ILLIQ_{i,t}$ and $AgILLIQ_t$ are the Amihud (2002) illiquidity and the aggregate Amihud (2002) liquidity in year t. Q, LSIZE, totaldebt, ROA, CAPX, TANG, RDAT, and CASH are respectively Tobin's Q, logarithm of market capitalization, total debt ratio, return on assets, capital expenditure ratio, tangible assets ratio, R&D expenditures to total assets, and cash holding ratio. HHI is the Herfindahl index, KZindex is Kaplan and Zingales (1997) index, and LAGE is logarithm of one plus firm age. ***, **, and * denotes a rejection of the null hypothesis at the 1%, 5%, and 10% level, respectively.

Different from the relationship between aggregate liquidity and firm innovation, the relationship between firm's stock liquidity and firm innovation is not persistent. Fang et al. (2013) use the sample from 1994 to 2005 and find that firm's stock liquidity impedes firm innovation. In contrast, Dass et al. (2012) document opposite effects of firm's stock liquidity and firm innovation. Moreover, Dass et al. (2012) point out two reasons why their results differ from those in Fang et al. (2013). First, because firm innovation is a non-stationary process, controlling for lag innovation is necessary when examining the effects of stock liquidity on firm innovation. Second, the sample period used in Fang et al. (2013) is quite "special", meaning that this sample period includes some years before and after the innovation peak, and the "years around decimalization 2000-2002 were years of economic slowdown"[15]. Thus, "it is not surprising that the change in patent applications over this period is strongly related to prior level of patenting and not including lagged levels would bias the results" (Dass et al. (2013)).

I use the longer sample period from 1976 to 2002 and document that my results support Dass et al.'s (2012) suggestions. As shown in table 16, when lag innovation proxies are not included in the regression models, stock liquidity is negatively related to future firm innovation, consistent with the findings by Fang et al. (2013). However, this relation becomes insignificant or even positive when lag innovation proxies are controlled. Moreover, besides two problems in Fang et al. (2013) pointed out by Dass et al. (2012), Hall et al. (2001, 2005, and 2009) show that the sample of some ending years of the database contain serious errors because almost all patents applied for had not yet

[15] More detail is shown in Dass et al. (2012).

appeared in the database. They suggest that the researchers should "take at least a 3-year "safety lag" when dating patents."

Table 16 also shows that the effects of some firm's characteristics on firm innovation depend on innovation proxy. Size and R&D expenditures are important characteristics to determine firm innovation. However, their effects on firm innovation are not persistent. Using the logarithm of number of patents or the logarithm of citation per patent to proxy for firm innovation, I document that both size and R&D expenditures are significantly positively correlated with firm innovation in future. This evidence implies that large firms or firms with high R&D expenditures tend to achieve a greater number of patents as well as more important patents. However, when the logarithm of number of patents or the logarithm of citation per patent are scaled by size, both size and R&D expenditures are significantly negatively correlated with firm innovation in the future. This means that small firms are more innovative. My evidence cautions the use of proxies for firm innovation in examining the relation between firm's characteristics and firm innovation.

I also check the relationship between stock liquidity and firm innovation captured by R&D expenditures. The results in table 17 show that that stock liquidity will enhance R&D investments. The t-statistics of the coefficients of both aggregate Amahud (2002) illiquidity and zero daily returns is from -7.66 to -5.68. Similarly, firm stock liquidity is also positively correlated with R&D investments. Furthermore, the aggregate stock market liquidity is positively correlated with firm R&D investments even after controlling for firm characteristics.

Table 17: Market Stock Liquidity and Firm R&D Investments

	(1) $RDAT_t$	(2) $RDAT_t$	(3) $RDAT_t$	(4) $RDAT_t$
$ILLIQ_{i,t}$	-0.001***	-0.001***		
	(-6.62)	(-6.62)		
$ZERO_t$			-0.042***	-0.042***
			(-9.24)	(-9.24)
$AgILLIQ_t$		-0.018***		
		(-7.66)		
$AgZERO_t$				-0.016***
				(-5.68)
$Q_{i,t-1}$	0.007***	0.007***	0.007***	0.007***
	(7.72)	(7.72)	(7.63)	(7.63)
$LSIZE_{i,t-1}$	-0.007***	-0.007***	-0.008***	-0.008***
	(-8.66)	(-8.66)	(-9.48)	(-9.48)
$Totaldebt_{i,t-1}$	-0.018***	-0.018***	-0.018***	-0.018***
	(-5.81)	(-5.81)	(-5.74)	(-5.74)
$ROA_{i,t-1}$	-0.007	-0.007	-0.009	-0.009
	(-0.79)	(-0.79)	(-1.08)	(-1.08)
$CAPX_{i,t-1}$	0.000	0.000	0.000	0.000
	(0.79)	(0.79)	(0.80)	(0.80)
$TANG_{i,t-1}$	0.017***	0.017***	0.017***	0.017***
	(4.54)	(4.54)	(4.59)	(4.59)
$LAGE_{i,t-1}$	-0.002	-0.002	-0.003**	-0.003**
	(-1.44)	(-1.44)	(-2.06)	(-2.06)
$RDAT_{i,t-1}$	0.648***	0.648***	0.646***	0.646***
	(12.50)	(12.50)	(12.50)	(12.50)
$CASH_{i,t-1}$	0.008**	0.008**	0.008**	0.008**
	(2.08)	(2.08)	(2.09)	(2.09)
$HHI_{i,t-1}$	0.001	0.001	0.001	0.001
	(0.63)	(0.63)	(0.55)	(0.55)
$Kzindex_{i,t-1}$	0.000	0.000	0.000*	0.000*
	(1.51)	(1.51)	(1.73)	(1.73)
_cons	0.036***	0.045***	0.050***	0.051***
	(8.43)	(9.09)	(10.15)	(10.22)
N	60,034	60,034	60,034	60,034
R^2	0.6780	0.6780	0.6777	0.6777

Notes: This table reports the results from the regression model of firm R&D investments on aggregate liquidity and other control variables for period is from 1976 to 2006. $ILLIQ_{i,t}$ and $ZERO_{i,t}$ are the Amihud (2002) illiquidity and zero daily return measures for firm i in year t. $AgILLIQ_t$ and $AgZERO_t$ are respectively the aggregate Amihud (2002) illiquidity and zero daily return measures in year t. Q, LSIZE, totaldebt, ROA, CAPX, TANG, RDAT, and CASH are respectively Tobin's Q, logarithm of market capitalization, total debt ratio, return on assets, capital expenditure ratio, tangible assets ratio, R&D expenditures to total assets, and cash holding ratio. HHI is the Herfindahl index, KZindex is Kaplan and Zingales (1997) index, and LAGE is logarithm of one plus firm age. ***, **, and * denotes a rejection of the null hypothesis at the 1%, 5%, and 10% level, respectively.

1.7. Conclusion

This essay investigates the effects of stock market liquidity on innovation for U.S. publicly traded firms at both the aggregate and the firm levels. I find that aggregate liquidity significantly affects aggregate innovation captured by aggregate number of patent applications or aggregate R&D expenditures. This finding indicates that aggregate innovation will improve when stock markets become more liquid and that aggregate stock liquidity is an important determinant of aggregate innovation.

I then provide two important underlying mechanisms for these effects. First, an increase in stock market liquidity will reduce the cost of raising external capital, thus encouraging firms, especially small firms or innovative ones, to issue more equity and debt to finance their innovation activity. Using aggregate R&D expenditures to proxy for aggregate innovation, I document that the relation between aggregate liquidity and aggregate R&D expenditures is stronger for a group of small firms.

Second, higher stock market liquidity increases firm valuation and reduces transaction costs, which motivates large firms to buy innovation from small firms through merger and acquisition activities. My essay shows that aggregate stock liquidity is significantly correlated with the merger and acquisition deals with patents as well as with the number of targets with patents. I also find that although the relation between aggregate liquidity and R&D expenditures are more pronounced for a group of small firms, I also show that the effect of aggregate liquidity on aggregate number of patents is stronger for the group of large firms. Moreover, I show that merger and acquisition activities with patents increase with stock market liquidity. This evidence indicates that small firms will invest

more in R&D when stock markets become more liquid, then will be acquired by large firms.

At firm level, these effects hold. Using several proxies for firm innovation: the log of number of patents scaled by size, the number of patents, the adjusted number of patent citations per patent scaled by size, as well as the adjusted number of patent citations per patent, and the ratio of R&D expenditures to total assets to capture firm innovation, I find that aggregate liquidity is significantly correlated with firm innovation. This result is also persistent when I use several models with different specifications.

These results contribute to the understanding of the link between finance and economic growth. A large amount of literature lists several factors affecting innovation as well as economic growth such as market competition, the world economy and international trade, human capital, etc. I complement these findings by examining the effects of stock market liquidity on innovation at both aggregate and firm levels as well as provide two important mechanisms that connect finance to economic growth. I also suggest a channel to link stock markets to firm valuation.

CHAPTER 2: STRATEGIC GROWTH OPTIONS, UNCERTAINTY AND R&D INVESTMENTS

2.1 Introduction

Under the real option framework (Pindyck (1991), Dixit and Pindyck (1994), and Abel et al. (1996)), firms invest less when facing high uncertainty. The reasoning behind this argument is that capital investments are (at least partially) irreversible and costly. Thus, when uncertainty increases, the value of option to wait will also go up, and firms tend to wait rather than immediately undertake capital investments to maximize their value. This approach has succeeded to explain the inverse relationship between capital investments and firms' idiosyncratic volatility (Leahy and Whited (1996), and Bulan (2005)).

Although the real options analysis has become a main stream in finance, it has often been based on two specific assumptions (Kulatilaka and Perotti (1998)): (1) a firm has a monopoly over an investment opportunity and (2) its action does not affect either the prices or market structure. These assumptions can be reasonable when the product markets are less competitive or monopolistic such as natural resource industries. However, they seem to be less realistic when the product markets become more competitive because other potential competitors can easily seize the growth opportunities. In such markets, it is usually recognized that early investment, especially R&D investment, is associated with greater ability to expand in the future. When a firm inaugurates a new product or a product with new technology, the value of other existing products in that market will deteriorate. For example, Nokia was the largest vendor of mobile phones in 1990s and at the beginning of 2000s. However, it lacked behind the

smartphone markets, causing its share price to fall from $40 in late 2007 to under $2 in mid-2012. In 2013, its mobile business was then acquired by Microsoft.

Due to these limitations in the standard real option framework, the current literature has relaxed these assumptions to examine the effects of uncertainty on firm's investment decision. Fudenberg and Tirole (1985) develop a model to show that firms can adopt a new technology sooner because of potential competitors. Grenadier (2002) documents that "exercise strategies cannot be determined separately but must be formed as part of a strategic equilibrium." Further, his model shows that the value of option to wait is drastically eroded due to competition and firms can invest at near the zero net present value threshold. More importantly, Kulatilaka and Perotti (1998) develop a strategic growth option model to show that under imperfect competition, uncertainty may encourage investment in growth options. The reasoning behind this model is that due to other potential competitors, not investing may lead another competitor to seize the opportunity while "immediate action may discourage entrants and enhance market share and profits" (Kulatilaka and Perotti (1998)). This theory also considers an initial investment as the acquisition of growth opportunities relative to other competitors, which allows the firm to take a competitive advantage. Moreover, under the imperfect competition environment, firm's profits are convex in demand. Therefore, when strategic investment has a significant preemptive effect, it will result in higher market share, and thus a greater convexity of ex post profits relative to the case of no investment in growth options. The greater convexity of profits will lead to high expected cash flows. As a

result, increased uncertainty can encourage investment in growth options when this strategic advantage is strong[16].

Although strategic growth option analysis theoretically predicts the positive relationship between uncertainty and firm's investments, the empirical evidence is still mixed. Minton and Schrand (1999) estimate cash flow volatility and average R&D investments during the same period and find that this relation is negative. Czarnitzki and Toole (2011) use the volatility of sales of innovative products as a proxy for uncertainty and document that this volatility is negatively related to R&D investments in absolute value. Stein and Stone (2012) re-examine this relationship and suggest that the negative relation between uncertainty and R&D investments may be caused by an endogeneity problem. Instrumenting for oil and currency prices and volatility, they find that uncertainty is positively related to R&D investments. However, they do not provide any explanation for this relationship[17].

In this essay, I apply the strategic growth option framework to examine the dynamic relationship between firms' R&D investments and firm uncertainty. Using the idiosyncratic volatility of stock returns to proxy for firm's uncertainty and considering

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[16] Although competitive advantage takes many forms, "a firm is said to have a competitive advantage when it is implementing a value creating strategy not simultaneously being implemented by any current or potential competitors" (Barney, 1991). Thus if firms want to enhance their competitive advantages, they must have some strategies which are valuable and difficult to imitate (Barney 1991, and Lengnick-Hall 1992). As shown in the literature on strategic management, R&D investments do well to generate firms' competitive advantages, because beyond their benefits mentioned above, the outcomes of these investments are difficult to imitate (Lengnick-Hall 1992). Importantly, this literature documents the firms' innovations as the cornerstones of their competitive advantages (Porter and Millar (1985), Barney (1991), and Lengnick-Hall (1992)).

[17] Stein and Stone (2012)'s "perhaps- reason" that uncertainty may increase the value of put options is opposite to the theoretical and empirical evidence documented in the literature (Dixit and Pindyck 1994, Abel et al. 1996, and Berger et al. 1996). If the value of put options increases, firms have more opportunities to sell capital assets at lower costs (Abel et al. (1996)). As a result, "the put option increases the incentive to invest" more in capital (Abel et al. (1996)), and thus reduces R&D investments to maximize a firm value, which is inconsistent to their empirical evidence.

the endogeneity problem in the relationship between firm's uncertainty and R&D, I uncover that, unlike capital investments, R&D investments increase with firm uncertainty. Consistent with the strategic growth options theory, I document that firm's uncertainty increases R&D investments[18] because R&D could potentially generate growth opportunities which enhance competitive advantages for firms in the future.

I further show that this strategic advantage is more important for less innovative firms or firms in more competitive industries because the competition and the fear of preemption drastically diminish the value of their options to wait. Consistent with this argument, I find that the positive relationship between uncertainty and change in R&D investments is more pronounced for these firms.

The effects of idiosyncratic volatility on corporate investment policies also depend on the firm's size. Seru (2010) and Phillips and Zhdanov (2012) document that large firms conduct less R&D (scaled by firm's size) than small ones; thus they are less innovative. Moreover, the strategic advantage is more valuable for the large firms because they have less operating flexibility. As a result, large firms tend to invest more in R&D and less in capital expenditures when their idiosyncratic volatility increases. My empirical evidence supports this hypothesis.

Although I estimate the stock idiosyncratic volatility in different windows, this volatility may be endogenous with corporate investment policies. Roberts and Whited (2012)

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[18] While both capital investments and R&D investments are important drivers for firm value and economic growth, R&D investments are different from capital investments in several ways. First, R&D investments usually drive the new technological progress and would generate the new physical capital and thus increase the productivity of physical investment (Lin, 2012). Second, while capital investments exercise or "kill" the real option to invest (Pindyck, 1991), R&D investments tend to generate growth options for the firm and enhance its competitive advantages in the future. This benefit of R&D investments is more pronounced under a competitive environment in which the value of growth options is easily expires.

document three main sources of endogeneity: simultaneity, omitted variables, and measurement errors. I am also concerned with these issues and address them by using different econometric methods as well as considering alternative measures to proxy for Tobin's Q.

First, it is possible that there is a causal relation between uncertainty and investments. Uncertainty can affect the change in investment policies and the change in investment strategies also lead to a change in idiosyncratic volatility in the future. On the one hand, firms with greater proportion of R&D investments in the future tend to have higher uncertainty because R&D investments are usually associated with new and untested technologies (Chan et al. (2001)). On the other hand, idiosyncratic volatility also affects corporate investment strategies. Because firms with high uncertainty will have a high value of option to wait, they may have incentives to invest in R&D rather than in capital expenditures since while capital investments exercise or "kill" real options to invest (Pindyck, 1991), R&D investments tend to generate growth options. Thus, this interactive relationship between idiosyncratic volatility and corporate investments calls for a simultaneous estimate. I use the simultaneous equation methods instead of panel data ones with firm-specific and time fixed effects.

Second, if Tobin's Q were an imperfect measure of investment opportunities, this would also lead to omitted variable bias in empirical estimate, and there may exist some latent variables affecting both uncertainty and investments. I employ instrumental variables for idiosyncratic volatility by using the market stock return volatility and the aggregate investments as well as some "internal" instruments: Tobin's Q, replacement costs, profitability, and stock returns. My intuition is that the effects of uncertainty on corporate

investments vary and may be impacted by macroeconomic variables. I find that uncertainty remains a statistically significant predictor of the change in corporate investments.

Different from current empirical literature on the effect of uncertainty on R&D investments (Minton and Schrand (1999), Czarnitzki and Toole (2011, and 2012), and Stein and Stone (2012)) which are mainly based on the real option analysis, my essay applies the strategic growth option framework to analyze the relationship between uncertainty and R&D investments. In addition, my essay is also largely related to the literature on innovation, firm characteristics, and competitive advantage (e.g. Eberhart et al. (2004), Seru (2010), and Phillips and Zhdanow, (2012)). However, while these studies focus on the benefits of R&D investments or the relation between firm characteristics and innovation, I investigate the effects of idiosyncratic volatility on R&D investment decisions.

To the best of my knowledge, this is the first empirical essay using the strategic growth option model to investigate the relationship between uncertainty and R&D investments. My essay also contributes to the literature on the effects of uncertainty on corporate investments by documenting that the incentives to enhance a firm's competitive advantage are main forces that drive the positive relation between a firm's idiosyncratic risk and its R&D investments.

The rest of the essay is organized as follow. The next section reviews literature and presents hypothesis development. Section 2.3 presents methodology and section 2.4 briefly introduces the data collection and descriptive statistics. In section 2.5, I examine the effects of uncertainty on corporate investment policies, and investigate the relation

between uncertainty, corporate investment policies and firms' characteristics in section 2.6. The relation between idiosyncratic volatility, corporate investment policies and industries will be examined in section 2.7. Section 2.8 documents the benefits of increase in R&D investments in reducing firms' idiosyncratic volatility in future. Section 2.9 will robustly test the results, and section 2.10 concludes.

2.2 Literature Review and Hypothesis Development

In the perfect capital markets, only the systematic component of risk is relevant for investment decisions. In contrast, a firm cannot fully diversify its operations in reality. As a result, both theoretical models and empirical evidence show that uncertainty matters for investment decisions. However, this literature focuses neither on the effects of idiosyncratic volatility on R&D investments nor on the change in corporate investment policies.

The literature on irreversible investments assumes that the adjustment costs are asymmetric and nonlinear with the costs of some input stocks. With adjustment costs, not investing allows firms to maintain its option to invest if the future business conditions become more attractive. When firms decide to make a capital investment decision, they will exercise or "kill" their options to wait (Pindyck 1991). Moreover, Dixit and Pindyck (1994) show that combination of uncertainty and irreversibility in investment will generate the region of inaction where a firm prefers to wait rather than immediately invest. Higher uncertainty enlarges this region and discourages investments. Thus, the relation between uncertainty and investments should be negative. Consistent with this hypothesis, Leahy and Whited (1996), and Bulan (2005) use stock return idiosyncratic

volatility to proxy for uncertainty and find that this volatility will depress capital investments.

This negative relation is also supported by the literature on managerial risk aversion (Panousi and Papanikolaou, 2012). A risk-averse investor will be concerned with un-diversifiable risk, thus will consider the covariance of a firm and market returns rather than variance of a firm's returns. By contrast, top executives hold undiversified stakes in their companies because they are not permitted to short their own stocks. Because investment decisions are made by top executives, if they are risk averse, they might underinvest when firm-specific uncertainty increases. Moreover, Panousi and Papanikolaou (2012) document that the negative relation between idiosyncratic risk and capital investments is more pronounced for firms with high managerial ownership.

In contrast to the traditional real option theory, the strategic growth option framework shows that the effect of uncertainty on investment is ambiguous under imperfect competition. This theory documents that although the value of not investing increases with rising uncertainty, the value of investing in growth option also increase due to the preemptive effects (Kulatilaka and Perotti (1998)). Thus, when these preemptive effects are high, increased uncertainty will lead to high investment.

Although R&D investment is an important driver for firm value and economic development, the effects of uncertainty on this investment is theoretically neglected. Bloom (2007) develops a model to show that R&D investments are very persistent because the marginal effect of uncertainty on R&D will be negative when firms increase R&D investments but be positive when firms reduce R&D investments. Thus, he calls for empirical research to examine this relation. Minton and Schrand (1999) calculate the cash

flow volatility over the six-year period and examine its impacts on the contemporaneous average corporate investments during the same period. They find that this cash flow volatility is contemporaneously negatively related to average capital investments, R&D and advertising. Although the results are interesting, this method also shows some weaknesses. First, the firm's characteristics may be different before or after it makes investment decisions, which could be problematic given that the average computation of these characteristics over a long period of time (6 years) may not show their true relation. For example, firms with low idiosyncratic risk will invest more, but when they invest more, their idiosyncratic volatility will increase (Duarte et al. (2011)). Second, the volatility may be endogenous with corporate investment policies (Roberts and Whited (2012)).

Czarnitzki and Toole (2007, 2011, and 2012) examine a panel of German manufacturing firms and find that firms will invest less in R&D when the absolute value when their sales of innovative products become more volatile. While the volatility of sales of innovative products may provide a good proxy for uncertainty, it may be highly correlated and endogenous with R&D investments and may not reflect the uncertainty of total sales or a firm's idiosyncratic risk. Further, they measure R&D investments in the log of absolute value of R&D, which may be dominated by firms with large R&D expenditures. Moreover, their estimated effects may be driven by the omitted control variables such as size, profitability or cash flow.

In contrast, Stein and Stone (2012) find that uncertainty captured by implied volatility from equity options will increase R&D investments by using "external" instrument variables (commodities prices). However, they just assume that the reason is perhaps that

the values of put options can offset the value of call options. This reason seems to be opposite to the theoretical and empirical evidence documented in the literature (Dixit and Pindyck (1994), Abel et al. (1996), and Berger et al. (1996)). When the value of put options increases, firms have more opportunities to sell capital assets at lower costs (Abel et al. (1996)). Moreover, because a firm's abandonment option is considered as a put option, Berger et al. (1996) find that firm value increases in exit value. As a result, "the put option increases the incentive to invest" more in capital (Abel et al. (1996)), and thus reduces R&D investments to maximize a firm value.

I, on the other hand, reexamine the effects of firm's uncertainty on its R&D investments and go a step further to examine these effects on corporate investment dynamics. Further, literature on strategic growth option suggests that firms may invest in growth options when uncertainty is high. Moreover, while capital investments exercise or "kill" option to invest (Pindyck (1991)), R&D investments tend to generate growth options and will reduce firms' specific risk in future. Thus, using idiosyncratic volatility to proxy for uncertainty, I come up with the following hypotheses:

Hypothesis 1: Firms tend to invest more in R&D when their idiosyncratic volatility is high because of the incentives to maintain and enhance their competitive advantage, all things equal.

Although firms have a high value in the options to wait when uncertainty is high, this value easily erodes due to potential competitors. This value deteriorates more for less innovative firms or firms in more competitive industries. Further, when idiosyncratic volatility is high, these firms become riskier and incentives to maintain their competitive advantage will increase. Therefore, I hypothesize:

Hypothesis 2: Less innovative firms and firms with less growth opportunities tend invest more in R&D but less in capital when their idiosyncratic volatility is high, all things equal.

Hypothesis 3: Firms in more competitive industries tend to invest more in R&D when their idiosyncratic volatility is high, all things equal.

Because endogeneity problems may affect any conclusion on the relationship between uncertainty and corporate investment policies, I use different econometric methods as well as considering alternative measures to proxy for Tobin's Q. The results will be shown in next sections.

2.3 Methodology

2.3.1 Measurement

I estimate the total volatility by calculating the annualized standard deviation of a firm's daily stock returns in a year. I then decompose the firm's total volatility into systematic and idiosyncratic volatilities as follows:

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the stock returns of firm i at date t, $R_{M,t}$ is the market returns at date t. My measure of idiosyncratic volatility is the standard deviation of residuals $\varepsilon_{i,t}$ over a year.

This measure is widely used to proxy for uncertainty in the literature on the effects of uncertainty on corporate investments (e.g. Leahy and Whited (1996), Bulan (2005), and Panousi and Papanikolaou (2012)). Because stock returns can reflect all firm's activities, this measure can capture the total uncertainty (Bulan (2005)). This measure also reflects the volatility of firm's profits and output price (Pindyck (1991)). Berk et al. (1999) and

Carlson et al. (2004), on the other hand, document that stock returns' volatility can reflect a firm's value of both assets in place and growth opportunities. Moreover, idiosyncratic volatility also reveals technological revolution (Pastor and Veronesi (2006, and 2009)). Thus, this measure is a good proxy for uncertainty that is relevant for firms' investment decisions.

An important issue in using idiosyncratic volatility is that this measure is highly persistent. Thus, I estimate it using non-overlapping window. This estimation is reasonable because corporate investments are often observed annually.

2.3.2 Specification

The goal of this essay is to examine the effects of firm uncertainty on corporate R&D investments. The orthodox theory of investment developed by Tobin (1969) compares the capitalized marginal investment to its purchase cost. If the ownership of investment is traded in the market, the capitalized value can be observed directly. Otherwise, this value is the expected value of the profits it will yield in future. Tobin (1969) uses the ratio of this value to the purchase price, called Tobin's Q, to govern the investment decisions. Thus, Tobin's Q should be controlled when I examine the effects of idiosyncratic volatility on corporate investment decisions.

Because replacement cost is not observed directly, I follow Salinger and Summers (1993) to estimate the replacement cost of capital. I then define Tobin's Q as the ratio of a firm's total market value to its replacement costs of capital. As shown in Salinger and Summers (1993), Tobin's Q almost reflects a firm's property plant and equipment. Thus, it is largely right skewed. To normalize this measure, I take the logarithm of this value.

Because both idiosyncratic volatility and corporate investments are affected by a firm's cash flows, size and leverage, these factors need to be controlled.

I follow Leahy and Whited (1996), Bulan (2005), and Panousi and Papaniolaou (2012) to investigate the effects of idiosyncratic volatility on corporate investment decisions by estimating the following regression:

$$Inv_{i,t} = \gamma_0 + \beta vol_{i,t-1} + \beta_1 logQ_{i,t-1} + \beta_2 \, logk_{i,t-1} + \beta_3 cfkl_{i,t-1} + \beta_4 \, bea_{i,t-1} + \beta_5 \, yret_{i,t-1} + \eta_i + g_t + e_{i,t} \quad (1)$$

where $Inv_{i,t}$ are capital investments (capital expenditures of firm i in year t/replacement costs of firm i in year t-1), R&D investments (R&D expenditures of firm i in year t/replacement costs of firm i in year t-1) or R&D investments/capital investments (R&D expenditures of firm i in year t / capital expenditures of firm i in year t). $Q_{i,t-1}$ is Tobin-Q defined as the ratio of a firm's market value to the replacement costs of capital in year t-1, $logk_{i,t-1}$ is log of a firm's replacement costs of capital to the average replacement costs of capital of all firms in the same industries in year t-1, $cfkl_{i,t-1}$ is the ratio of cash flow to cost of capital in year t-1(operating income in year t-1/replacement costs in year t-2), $bea_{i,t-1}$ is the book equity ratio of firm i in year t-1, and $yret_{i,t-1}$ is yearly stock returns of firm i in year t-1. η_i is firm dummies and g_t is time dummies.

Due to an endogeneity problem in the relation between idiosyncratic volatility and corporate investments, I consider different methods to examine the effects of uncertainty on corporate investment decisions. Roberts and Whited (2012) document three main sources of endogeneity-simultaneity, omitted variables and errors in measurement. In this

paper, I consider these problems when investigating the relationship between idiosyncratic risk and corporate investments.

Simultaneous equation systems (SE):

First, I consider the simultaneous equation estimation. As shown in previous sections, idiosyncratic volatility can affect corporate investments, and the change in corporate investment policies also results in change in future idiosyncratic volatility. I modify equation (1) by adding another regression model of a firm's idiosyncratic volatility on investment ratios and other firm's characteristics (2b). In this equation, I control for both capital and R&D investments. In detail, I estimate the effects of idiosyncratic volatility on corporate investment decisions by considering the following equation systems:

$$Inv_{i,t} = \gamma_0 + \beta vol_{i,t-1} + \beta_1 Q_{i,t-1} + \beta_2 \log k_{i,t-1} + \beta_3 cfkl_{i,t-1} + \beta_4 bea_{i,t-1} + \beta_5 yret_{i,t-1} + \eta_i + g_t + e_{i,t} \quad (2a)$$

$$vol_{i,t-1} = \gamma_0 + \beta_1 Q_{i,t-1} + \beta_2 \log k_{i,t-1} + \beta_3 cfkl_{i,t-1} + \beta_4 bea_{i,t-1} + \beta_5 yret_{i,t-1} + \beta Inv_{i,t} + \gamma volm_{t-1} + \eta_i + g_t + e_{i,t} \quad (2b)$$

Instrumental variables (IV):

Second, because I do not have general measures of uncertainty and of investment opportunities, I can use instrumental variables to reduce the effects of latent variables on the relation between idiosyncratic volatility and corporate investments. I use two external variables: the aggregate capital investment ratio and stock market return volatility to instrument for a firm's idiosyncratic volatility.

$vol_{i,t-1} = \gamma_0 + \gamma_1 ainv_{t-1} + \gamma_2 volm_{t-1} + \beta_1 Q_{i,t-1} + \beta_2 \log k_{i,t-1} + \beta_3 cfkl_{i,t-1} + \beta_4 \, bea_{i,t-1} + \beta_5 \, yret_{i,t-1} + \eta_i + g_t + e_{i,}$(3a)

$Inv_{i,t} = \gamma_0 + \beta vol_{i,t-1} + \beta_1 Q_{i,t-1} + \beta_2 \log k_{i,t-1} + \beta_3 cfkl_{i,t-1} + \beta_4 \, bea_{i,t-1} + \beta_5 \, yret_{i,t-1} + \eta_i + g_t + e_{i,t}$ (3b)

I measure the R&D investment ratio as a firm's R&D expenditures to its replacement cost of capital. However, some recent studies use the ratio of a firm's R&D expenditures to its total assets or sales (e.g. Chan et al. (2001), Kothari et al. (2002), and Eberhart et al. (2008)). Thus, I robustly check the effects of idiosyncratic volatility on corporate investment decisions by using different measures of R&D investments.

2.4 Data, Measures and Descriptive Statistics

2.4.1 Data and Measures

I collect stock returns, prices, and number of shares outstanding from the Center for Research in Security Prices (CRSP) daily tapes for all ordinary common stocks (share code of 10 and 11) from 1980 to 2010. I use firms' daily stock returns to estimate a firm's total volatilities and its idiosyncratic volatility. I compute the yearly returns by calculating geometric average of stock returns during a year.

I use COMPUSTAT files to calculate capital investment ratio, R&D investment ratio, the replacement cost of capital, Tobin's Q, operating cash flow ratio, and the ratio of book equity to total assets from 1980 to 2010. I use the price deflator for non-residential fixed investment from National Income and Product Accounts (NIPA) to estimate a firm's replacement cost of capital. I define Tobin's Q as the ratio of a firm's market capitalization at the end of December plus book value of long term debt and of preferred

stock, minus inventories to its replacement cost of capital. I compute operating cash flow ratio as the ratio of a firm's operating income to its replacement cost of capital. These variables are discussed in table 18.

Table 18: Variable Definition and Calculation

Variable	Definition and Calculation
$Vol_{i,t-1}$	idiosyncratic volatility of stock returns of firm i in year t-1
$Invest_{i,t}$	capital investments (capital expenditures of firm i at time t/replacement costs of firm i in year t-1)
$rdin_{i,t}$	R&D investments (R&D expenditures of firm i at time t/replacement costs of firm i in year t-1)
$Rd/(cap+rd)_{i,t}$	R&D investments/total investments (R&D expenditures of firm i at time t / both capital and R&D expenditures of firm in year t)
$Logk_{i,t-1}$	log of a firm's replacement costs of capital to the average replacement costs of capital of all firms in the same industries in year t-1. I follow the methodology of Salinger and Summers (1983) and use the perpetual inventory method to compute the replacement value of the capital stock. I initialize the first value of capital stock (K_0) as gross PPE. I then construct the capital stock iteratively as $K_t = ((P_t/P_{t-1})^* K_{t-1} + I_t)(1-\delta_j)$, where P is the price deflator for fixed nonresidential investment from National Income and Product Accounts, I is capital expenditure, and δ_j is book depreciation rate at the three-digit SIC level. I calculate $\delta_j = 2/L_j$, where L_j is the useful life of capital good, computed as $L_j = \frac{1}{N_j} \sum_{i \in j} \frac{PPE_{t-1}+I_t}{D_t}$.
$Q_{i,t-1}$	Tobin-Q defined as the ratio of a firm's market value to the replacement costs of capital in year t-1. The firm's market value is the market value of equity, plus book value of debt, plus book value of preferred stock and minus inventories.
$Cfkl_{i,t-1}$	the ratio of operating income to cost of capital in year t-1 (operating income at time t-1/replacement costs in year t-2)
$Bea_{i,t-1}$	the book equity ratio of firm i in year t-1
$yret_{i,t-1}$	yearly stock returns of firm i in fiscal year t-1
$Volm_{t-1}$	stock market returns volatility in year t-1

Following Pastor and Veronesi (2003), I exclude any observation with market to book less than 0.01 or greater than 100. I eliminate any observation with total assets and market capitalization and book value less than $1 million, or any observation with return on equity greater than 100 or less than -100. Financial, utility and other regulated companies are also excluded from my sample[19]. Further, any observation without replacement cost of capital or with replacement cost of capital of zero are also eliminated from the sample. My final sample consists of 78,126 firm-year observations.

2.4.2 Descriptive Statistics

Table 19 shows the descriptive statistics of sample firms. Because I investigate corporate investment policies under uncertainty, I focus on two types of investments- capital investments and R&D expenditures. As shown in table 19, the average of a firm's capital expenditure is 0.286 and its median is 0.202. On the other hand, the average of a firm's R&D expenditures to its replacement cost of capital is 0.357 while this value at 75th percentile is 0.279. This evidence shows that R&D investments are clustered in some groups of firms. As documented in literature (e.g. Chan et al. (2001), and Eberhart et al. (2004)), R&D expenditures almost belong to firms in high –tech industries[20]. Therefore I winsorized both capital and R&D investments at the 1st and 99th percentiles to reduce outliers.

I calculated Tobin's Q as the ratio of market value of a firm to its physical replacement costs. Because physical replacement costs are basically the costs to replace physical assets (e.g. property, plant, and equipment), these costs are low for firms with high R&D investments. As a result, Tobin's Q is high for these firms. Thus, to reduce right

[19] The industries are taken from Barclay and Smith (1995)
[20] Industries defined in section

skewness toward firms with high R&D, I use the log form of this variable. As shown in table 19, the mean of Tobin's Q for firms in my sample is 1.403, while its median is 1.311.

Table 19: Firms' Characteristics

Variable	Mean	Median	25th Pctl	50th Pctl	75th Pctl	N
LAT	5.079	4.952	3.570	4.952	6.475	78,126
lsize	5.004	4.879	3.421	4.879	6.468	78,126
MB	2.727	1.753	1.079	1.753	2.987	78,126
invest	0.286	0.202	0.108	0.202	0.353	78,126
rdin	0.357	0.000	0.000	0.000	0.279	78,126
vol	0.035	0.029	0.020	0.029	0.043	78,126
Q	12.430	3.710	1.482	3.710	10.302	78,126
logq	1.403	1.311	0.394	1.311	2.332	78,126
Logk	-2.524	-2.653	-4.157	-2.653	-1.018	78,126
cfkl	0.002	0.129	-0.020	0.129	0.405	78,126
bea	0.538	0.532	0.385	0.532	0.701	78,126
yret	0.198	0.060	-0.219	0.060	0.389	78,126
age	16.62	12	6	12	22	78,126

Notes: This table shows the characteristics of all firms in my sample during the period of time from 1980 to 2011. LAT is the log of total assets, Lsize is the log of firm's market capitalization, MB is the ratio of firm's size to its book equity, Invest is a firm's capital investments to its replacement costs, rdin is a firm's R&D investment to its replacement costs, and vol is a firm's idiosyncratic volatility. Q is Tobin's Q, logq is log of Tobin's Q, cfkl is the ratio of operating income to cost of capital, bea is the book equity ratio, and yret is yearly stock returns. Age is firm age.

The results in table 19 show that the average stock return idiosyncratic volatility is 0.035 and its median is 0.029. The average of firms' log total assets in my sample is 5.079 while the median is 4.952. The average of log size captured by market capitalization is 5.004. The average book equity to total assets is 0.538 while its median is 0.532.

2.5 Uncertainty and Corporate Investment Policies

Recent literature (e.g. Pindyck 1991, Dixit Pindyck (1994), and Panousi and Papanikolaou, (2012)) widely documents the effects of idiosyncratic volatility on capital

investments; however, these effects on R&D investments or corporate investment policies are relatively unexplored. In this section, I will investigate the changes in a firm's investment policies under uncertainty. I focus on two important types of corporate investments- capital and R&D. First, I examine the effects of idiosyncratic volatility on a firm's R&D investment proportion to its total investments. Second, I study these effects on a firm's capital and R&D investments.

As shown in the previous section, this idiosyncratic volatility measure may be endogenous with corporate investments. I use three different econometric methods to estimate the effects of a firm's idiosyncratic volatility on its investment policies: fixed effects, simultaneous equation estimation and instrumental variables. Because my purpose is to examine the effects of a firm's idiosyncratic volatility on its investment policies, I mainly focus on the main results from the simultaneous equation estimation (model 2a).

Table 20 shows the results from the regressions of a firm's R&D investment proportion to total investments on its idiosyncratic volatility and other firm's characteristics. Consistent with my first hypothesis, the results from three models show that a firm's idiosyncratic volatility is significantly positively correlated with R&D investment proportion. The-statistics of these coefficients are greater than 3.6. Similarly, the change in firm idiosyncratic volatility is also positively correlated with the ration of R&D investments to total corporate investments. Consistent with my hypothesis, these results show that when a firm's uncertainty increases, it tends to invest more in R&D than in capital expenditures.

Table 20: Stock Idiosyncratic Volatility and Corporate Investments

Model	(1)	(2)	(2a)	(2b)	(2a)	(2b)	(3)
	$Rd/(cap+rd)_{i,t}$	$Rd/(cap+rd)_{i,t\,t}$	$Rd/(cap+rd)_{i,t}$	$Vol_{i,t-1}$	$Rd/(cap+rd)_{i,t}$	$Cvol_{i,t-1}$	$Rd/(cap+rd)_{i,t}$
$Vol_{i,t-1}$	0.187***		4.546***				2.517***
	(3.68)		(74.47)				(6.61)
$Cvol_{i,t-1}$		0.101***			1.143***		
		(3.02)			(15.43)		
$Logq_{i,t-1}$	-0.013***	-0.014***	0.085***	-0.005***	0.069***	-0.001***	0.078***
	(-9.08)	(-9.74)	(89.55)	(-77.59)	(74.17)	(-15.97)	(30.40)
$Logk_{i,t-1}$	-0.009***	-0.009***	0.005***	-0.005***	-0.020***	-0.000***	-0.006**
	(-3.63)	(-3.96)	(8.17)	(-171.87)	(-37.35)	(-11.92)	(-2.41)
$cfkl_{i,t-1}$	-0.001**	-0.001**	-0.005***	-0.000***	-0.006***	-0.000***	-0.006***
	(-2.27)	(-2.31)	(-19.50)	(-18.45)	(-25.98)	(-5.56)	(-3.80)
$bea_{i,t-1}$	-0.013*	-0.014**	0.297***	-0.011***	0.266***	-0.003***	0.285***
	(-1.78)	(-2.00)	(52.43)	(-34.60)	(46.66)	(-10.03)	(19.12)
$yret_{i,t-1}$	-0.006***	-0.006***	-0.037***	0.003***	-0.025***	-0.000***	-0.033***
	(-8.09)	(-7.66)	(-28.34)	(38.41)	(-19.62)	(-4.18)	(-16.54)
_cons	0.219***	0.224***	-0.104***	0.011***	-0.027***	-0.011***	-0.088***
	(22.08)	(23.00)	(-15.22)	(22.54)	(-3.96)	(-26.33)	(-6.45)
Method	F, T, OLS	F, T, OLS	SE	SE	SE	SE	IV, 2SLS
N	77,670	77,670	77,670	77,670	77,670	77,670	77,670
R^2	0.0110	0.0071	0.2214	0.3886	0.2203	0.0961	0.2287

Notes: This table presents the results from the regression models 1, 2, and 3. $Vol_{i,t-1}$ is a firm's idiosyncratic volatility in year t-1. $Cvol_{i,t-1}$ is the change in idiosyncratic volatility for firm i from year t-2 to t-1. logq is log of Tobin's Q, cfkl is the ratio of operating income to cost of capital, bea is the book equity ratio, and yret is yearly stock returns. F denotes firm fixed effects, T denotes time fixed effects, SE denotes simultaneous equation method, and IV denotes instrumental variables. The standard errors are clustered at the firm-level, and t-statistics are reported in parentheses. *** (**) (*) indicates significance at the 1%, (5%), (10%) two-tailed level.

While the effects of a firm's idiosyncratic volatility on its R&D investment proportion are consistent among the three models, the effects of some other firm's characteristics are inconsistent among these models. The results from the fixed effect method show that Tobin's Q (in the log form) is negatively related to its R&D investment proportion, while this relation is positive in other models. While the results from simultaneous equation estimation show the positive relation between the physical replacement costs and the R&D proportion, this relation is negative in fixed effect model and instrumental variable estimation. Similarly, while the ratio of book equity on total assets is insignificantly correlated with R&D investment proportion in the fixed effect model, but it is significantly positively related to R&D investment proportion in other regression specifications.

In contrast, all three models show that a firm's profitability and stock returns are significantly negatively correlated with its R&D investment proportion. These results imply that firms with high profitability and have good performance tend to invest more in capital expenditures rather than in R&D.

To further examine the effects of a firm's uncertainty on its corporate investment policies, I estimate regressions of capital and R&D investments on a firm's idiosyncratic volatility and other characteristics. Current literature widely documents the negative relation between a firm's idiosyncratic volatility and its capital investments. Real option theory documents that capital investments are irreversible and costly and that uncertainty will generate options to wait. Thus, firms will delay these investments when their uncertainty is high to maximize their value (e.g. Pindyck (1991), Dixit Pindyck (1994)). The negative relation between idiosyncratic volatility and capital investments can also be

explained by managerial risk aversion behaviors (Panousi and Papanikolaou, (2012)). Because top executives are risk averse due to the inability to short their company's shares, they will invest less when a firm's idiosyncratic risk is high.

Consistent with these theories, the results in table 21 show that firm's idiosyncratic volatility is significantly negatively related to capital investments. The t-statistic of this coefficient in both models is less than -13. Further, these results document that firms with high Tobin's Q, high profitability, and good performance tend to invest more while firms with high replacement costs will invest less in capital expenditures.

This result is also consistent with my hypothesis that incentives to maintain and enhance a firm's competitive advantage mainly drive its investment policies. As analyzed in the previous section, idiosyncratic volatility will generate options to wait. If this value is higher than the benefits of capital investments, a firm should delay these investments to optimize its total value and enhance its competitive advantage.

In contrast with the negative relationship between idiosyncratic volatility and capital investments, firm's idiosyncratic volatility is significantly positively correlated with firm's R&D investments. Because R&D investments are risky, this positive relation is inconsistent with the managerial risk aversion hypothesis. Moreover, R&D investments are even more irreversible and costly (Li, 2011), and the literature on real options, which focuses on the costs of irreversible and the value of options to wait, does not seem to explain the relation between firm's idiosyncratic volatility and its R&D investments. However, the value of the option to wait is easily eroded because of potential competitors or an increase in cost of capital. In this case, firms may not get high value from high idiosyncratic volatility if they do not maintain or generate growth opportunities. Thus,

under competition environment, the effects of idiosyncratic volatility on R&D investments become ambiguous.

Using the strategic growth option framework, I hypothesize that the positive relation between firm's idiosyncratic volatility and its R&D investments is caused by the incentives to maintain and enhance its competitive advantage. As documented in the literature, R&D investments usually result in a new technological progress and will increase the productivity of physical investment (Lin (2012)). Because the outcomes of R&D investments are difficult to imitate (Lengnick-Hall 1992), these investments are considered as the cornerstones of their competitive advantages (Porter and Millar (1985), Barney (1991), and Lengnick-Hall (1992)). Eberhart et al. (2004) empirically find that firms with substantial increase in R&D expenditures will outperform in future. Similarly, Pindyck (1991) documents that R&D investments with generate more growth opportunities and then enhance firms' competitive advantages.

The results in table 21 are consistent with my hypothesis. Firms with low profitability and with low stock returns tend to invest more in R&D. T-statistics of coefficients in both the estimation methods are less than -4. Moreover, the equity ratio is significantly and positively related with R&D investments, while this ratio is negatively correlated with capital investments. Similarly, while firms with good performance (high profitability or high stock returns) last year tend to make more capital investments, they will invest less in R&D. Because the effects of these firm's characteristics on R&D are opposite to these effects on capital investments, it implies that R&D investments are different from capital investments as discussed in the previous section.

Table 21: Stock Idiosyncratic Volatility and Capital and R&D Investments

Model	(2a)	(2a)	(3a)	(2a)	(2a)	(3a)
	$Invest_{i,t}$	$Invest_{i,t}$	$Invest_{i,t}$	$rdin_{i,t}$	$rdin_{i,t}$	$rdin_{i,t}$
$Vol_{i,t-1}$	-0.870***		-3.463***	7.715***		6.809***
	(-16.37)		(-13.42)	(54.05)		(8.33)
$Cvol_{i,t-1}$		-0.872***			0.854***	
		(-13.77)			(4.98)	
$Logq_{i,t-1}$	0.089***	0.092***	0.076***	0.275***	0.247***	0.271***
	(108.60)	(114.78)	(51.48)	(123.95)	(113.86)	(34.32)
$Logk_{i,t-1}$	-0.004***	0.000	-0.020***	0.000	-0.044***	-0.004
	(-7.55)	(0.96)	(-12.37)	(0.14)	(-34.49)	(-0.86)
$cfkl_{i,t-1}$	0.003***	0.003***	0.002***	-0.024***	-0.027***	-0.025***
	(14.46)	(15.71)	(3.77)	(-42.46)	(-47.41)	(-4.50)
$bea_{i,t-1}$	-0.005	-0.001	-0.030***	0.474***	0.419***	0.473***
	(-1.10)	(-0.18)	(-3.45)	(35.85)	(31.59)	(15.96)
$yret_{i,t-1}$	0.033***	0.031***	0.040***	-0.045***	-0.027***	-0.045***
	(29.58)	(27.46)	(19.30)	(-15.04)	(-9.00)	(-9.15)
_cons	0.206***	0.191***	0.256***	-0.405***	-0.276***	-0.515***
	(34.93)	(32.64)	(29.94)	(-25.42)	(-17.46)	(-17.73)
Method	SE	SE	IV, 2SLS	SE	SE	IV, 2SLS
N	78,126	78,126	78,126	78,126	78,126	78,126
R^2	0.2251	0.2251	0.1659	0.3034	0.3031	0.3021

Notes: This table presents the results from the regression models 2 and 3. $Invest_{i,t}$ is the capital investment ratio which is the value of capital expenditures to replacement costs. $rdin_{i,t}$ is the ratio of R&D investments to replacement costs. $Vol_{i,t-1}$ is a firm's idiosyncratic volatility in year t-1. $Cvol_{i,t-1}$ is the change in idiosyncratic volatility for firm i from year t-2 to t-1. logq is log of Tobin's Q, cfkl is the ratio of operating income to cost of capital, bea is the book equity ratio, and yret is yearly stock returns. SE denotes simultaneous equation method, and IV denotes instrumental variables. The standard errors are clustered at the firm-level, and t-statistics are reported in parentheses. *** (**) (*) indicates significance at the 1%, (5%), (10%) two-tailed level.

2.6 Uncertainty, Investment Policies and Firm's Characteristics

Section 2.5 documents that firms tend to invest more in R&D when their idiosyncratic volatility is high because they want to maintain and enhance their competitive advantages. In this section, I further examine the effects of firm's characteristics on the relation between a firm's uncertainty and its investment policies.

If the incentives to maintain and enhance a firm's competitive advantage are the main driver of the positive relationship between uncertainty and its R&D investments, I should expect that this relationship is more pronounced for firms with higher incentives. Because less innovative firms or firms with low growth opportunities tend to have higher incentives to maintain their competitive advantages, I expect that the effects of idiosyncratic volatility on R&D investments will be high for these firms.

Following Chan et al. (2001), Eberhart et al. (2004) and Eberhart et al. (2008), I use the ratio of R&D expenditures to total assets or total sales (not reported) to capture a firm's innovative level. The higher this ratio is, the more innovative a firm is.

Because Q-theory of investments states that firms with high Tobin' Q will invest more and this measure also can be used to capture a firm's growth opportunities (e.g. Cao et al. (2008)), I use market–to–book ratio to proxy for growth opportunities to avoid unnecessary misunderstanding. This variable is widely used in the literature (e.g. Cao et al. (2008)). I also use R&D investments to total assets to capture innovation and book equity to total assets to capture a firm's capital structure.

Another firm's characteristic widely used to study the relation between firm's characteristics and innovation is firm's size. Although large firms have high absolute

values of R&D investments and patents, they have lower innovation scaled by size (Seru (2010), and Phillips and Zhdanov (2012)). Thus, they are less innovative than small ones. As a result, I expect that they will invest more in R&D and less in capital expenditures when their idiosyncratic volatilities are high.

Table 22 presents the results from the regression models of R&D investment proportion to total corporate investments on these firm's characteristics and other firm characteristics. These results show that less innovative firms tend to invest more in R&D when their specific risk is high. Firms with less growth opportunities captured by market-to-book ratio also tend to invest more in R&D. Consistent with my hypothesis, large firms or less innovative firms tend to invest more in R&D when their idiosyncratic volatility is high. The absolute values of t-statistics of these coefficients are greater than 11. Table 22 also shows that the relation between firm's uncertainty and its R&D investment proportion is more pronounced for firms with high equity financing.

Because the change in R&D investment proportion can result from the change in R&D or in capital expenditure or both, I examine the effects of these firm's characteristics on the relation between idiosyncratic volatility and capital and R&D investments. These results are shown in tables 23 and 24.

Table 23 presents the effects of these firm's characteristics on the relation between firm's idiosyncratic volatility and capital investments. The results in this table show that firms with high R&D investment ratio or firms with high equity financing tend to invest less, while large firms tend to invest more in capital expenditure when they face high idiosyncratic volatility. However, these firm's characteristics do not affect the relation between firm idiosyncratic volatility and the change in capital investments.

Table 22: Stock Idiosyncratic Volatility, Corporate Investments, and Firm's Characteristics

	$Rd/(cap+rd)_{i,t}$	$Rd/(cap+rd)_{i,t}$	$Rd/(cap+rd)_{i,t}$	$Rd/(cap+rd)_{i,t}$	$Rd/(cap+rd)_{i,t}$	$Rd/(cap+rd)_{i,t}$	$Rd/(cap+rd)_{i,t}$
$Vol_{i,t-1}$	4.272***	2.591***	3.623***	2.399***	2.028***	4.514**	2.089***
	(63.23)	(5.58)	(69.66)	(6.81)	(15.33)	(2.45)	(21.68)
$Vol*MB_{i,t-1}$	-0.107***	-0.016					
	(-10.50)	(-0.42)					
$MB_{i,t-1}$	0.009***	0.005***					
	(16.77)	(2.99)					
$Vol*RDAT_{i,t-1}$			-25.576***	-23.294***			
			(-76.12)	(-10.92)			
$RDAT_{i,t-1}$			3.331***	3.236***			
			(160.29)	(22.97)			
$Vol*bea_{i,t-1}$					0.918***	-3.026	
					(4.38)	(-1.11)	
$Vol*lsize_{i,t-1}$							0.408***
							(15.27)
$lsize_{i,t-1}$							0.109***
							(41.16)
$Logq_{i,t-1}$	0.076***	0.072***	0.047***	0.043***	0.078***	0.079***	-0.031***
	(73.99)	(27.20)	(61.20)	(20.49)	(81.50)	(28.81)	(-12.04)
$Logk_{i,t-1}$	0.002***	-0.006**	0.005***	-0.001	-0.007***	-0.003	-0.116***
	(2.94)	(-2.36)	(10.37)	(-0.46)	(-10.14)	(-1.00)	(-45.86)
$cfkl_{i,t-1}$	-0.005***	-0.005***	0.001***	0.001**	-0.005***	-0.006***	-0.005***
	(-19.87)	(-3.78)	(6.54)	(1.97)	(-22.41)	(-3.82)	(-22.03)
$bea_{i,t-1}$	0.311***	0.303***	0.177***	0.172***	0.247***	0.404***	0.178***
	(53.94)	(19.94)	(39.29)	(14.63)	(24.96)	(3.67)	(29.65)
$yret_{i,t-1}$	-0.037***	-0.036***	-0.020***	-0.018***	-0.032***	-0.033***	-0.040***
	(-27.84)	(-18.38)	(-19.21)	(-12.31)	(-24.88)	(-17.11)	(-30.87)
Method	SE	SE	SE	SE	SE	SE	SE
N	77,670	77,670	77,670	77,670	77,670	77,670	77,670
R^2	0.2278	0.2309	0.5159	0.5175	0.2349	0.2227	0.2566

Notes: This table presents the results from the regression model 2. $Vol_{i,t-1}$ is a firm's idiosyncratic volatility in year t-1. $Rd/(cap+rd)_{i,t}$ is the ratio of R&D investments to total investments. MB is the ratio of firm's size to its book equity, RDAT is the ratio of R&D investments to total assets, bea is the ratio of firm's equity to total assets, and lsize is log of a firm's market capitalization. Other control variables are defined in appendix. The standard errors are clustered at the firm-level, and t-statistics are reported in parentheses. *** (**) (*) indicates significance at the 1%, (5%), (10%) two-tailed level.

Table 23: Stock Idiosyncratic Volatility, Firm's Characteristics, and Capital Expenditures

	$invest_{i,t}$	$cinvest_{i,t}$	$invest_{i,t}$	$cinvest_{i,t}$	$invest_{i,t}$	$cinvest_{i,t}$	$invest_{i,t}$	$cinvest_{i,t}$
$Vol_{i,t-1}$	-0.390***	-0.260	-0.173***	0.083	-0.351***	-0.675**	-3.015***	0.105
	(-6.64)	(-1.58)	(-3.03)	(0.52)	(-3.08)	(-2.11)	(-35.96)	(0.44)
$Vol*MB_{i,t-1}$	-0.065***	0.002						
	(-7.36)	(0.08)						
$MB_{i,t-1}$	0.001***	-0.003**						
	(2.95)	(-2.49)						
$Vol*RDAT_{i,t-1}$			-2.412***	0.420				
			(-6.55)	(0.40)				
$RDAT_{i,t-1}$			-0.131***	-0.357***				
			(-5.75)	(-5.56)				
$Vol*bea_{i,t-1}$					-0.930***	0.493		
					(-5.15)	(0.97)		
$Vol*lsize_{i,t-1}$							0.759***	-0.092
							(32.57)	(-1.40)
$lsize_{i,t-1}$							0.014***	0.009
							(5.83)	(1.38)
$Logq_{i,t-1}$	0.092***	0.069***	0.095***	0.071***	0.090***	0.064***	0.057***	0.060***
	(102.80)	(27.55)	(112.91)	(29.98)	(108.75)	(27.83)	(25.70)	(9.51)
$Logk_{i,t-1}$	-0.003***	-0.012***	-0.002***	-0.012***	-0.004***	-0.013***	-0.033***	-0.018***
	(-4.72)	(-7.61)	(-3.78)	(-7.42)	(-6.86)	(-8.17)	(-15.14)	(-2.90)
$cfkl_{i,t-1}$	0.003***	-0.000	0.002***	-0.001*	0.003***	-0.000	0.003***	-0.000
	(14.25)	(-0.30)	(11.02)	(-1.74)	(14.25)	(-0.06)	(16.14)	(-0.06)
$bea_{i,t-1}$	-0.009*	-0.063***	0.009*	-0.033**	0.031***	-0.071***	-0.044***	-0.055***
	(-1.73)	(-4.52)	(1.85)	(-2.36)	(3.59)	(-2.95)	(-8.28)	(-3.68)
$yret_{i,t-1}$	0.035***	0.061***	0.031***	0.056***	0.033***	0.059***	0.026***	0.059***
	(30.37)	(19.09)	(27.56)	(17.94)	(29.71)	(18.82)	(23.20)	(18.53)
N	78,126	78,126	78,126	78,126	78,126	78,126	78,126	78,126
R^2	0.2269	0.0280	0.2326	0.0294	0.2254	0.0278	0.2281	0.0278

Notes: This table presents the results from the regression model 2. $Vol_{i,t-1}$ is a firm's idiosyncratic volatility in year t-1. $Invest_{i,t}$ is the capital investment ratio which is the value of capital expenditures to replacement costs. $cinvest_{i,t}$ is the change in capital investment to replacement costs at the previous year. MB is the ratio of firm's size to its book equity, RDAT is the ratio of R&D investments to total assets, bea is the ratio of firm's equity to total assets, and lsize is log of a firm's market capitalization. Other control variables are defined in appendix (not reported here). The standard errors are clustered at the firm-level, and t-statistics are reported in parentheses. *** (**) (*) indicates significance at the 1%, (5%), (10%) two-tailed level.

Table 24: Stock Idiosyncratic Volatility, Firm's Characteristics, and R&D Investments

	$rdin_{i,t}$	$crd_{i,t}$	$rdin_{i,t}$	$crd_{i,t}$	$rdin_{i,t}$	$crd_{i,t}$	$rdin_{i,t}$	$crd_{i,t}$
$Vol_{i,t-1}$	6.510***	0.690***	4.548***	3.072***	-0.581*	-0.790	-3.410***	-2.427***
	(41.24)	(2.64)	(36.61)	(12.07)	(-1.89)	(-1.56)	(-15.14)	(-6.47)
$Vol*MB_{i,t-1}$	-0.046*	0.002						
	(-1.95)	(0.05)						
$MB_{i,t-1}$	0.013***	0.005**						
	(9.76)	(2.33)						
$Vol*RDAT_{i,t-1}$			-44.364***	-16.698***				
			(-55.15)	(-10.15)				
$RDAT_{i,t-1}$			6.923***	0.449***				
			(139.13)	(4.41)				
$Vol*bea_{i,t-1}$					7.944***	2.155***		
					(16.34)	(2.68)		
$Vol*lsize_{i,t-1}$							2.532***	0.868***
							(40.46)	(8.33)
$lsize_{i,t-1}$							0.035***	-0.027**
							(5.63)	(-2.57)
$Logq_{i,t-1}$	0.256***	0.056***	0.188***	0.072***	0.259***	0.061***	0.162***	0.061***
	(106.49)	(14.05)	(102.80)	(19.19)	(116.86)	(16.62)	(27.14)	(6.20)
$Logk_{i,t-1}$	-0.007***	0.001	-0.003**	0.008***	-0.025***	-0.002	-0.110***	0.004
	(-4.87)	(0.30)	(-2.45)	(3.39)	(-16.51)	(-0.72)	(-18.62)	(0.40)
$cfkl_{i,t-1}$	-0.024***	0.017***	-0.010***	0.016***	-0.025***	0.017***	-0.025***	0.017***
	(-42.42)	(18.07)	(-22.22)	(16.52)	(-44.40)	(17.81)	(-43.29)	(18.06)

Table 24: Stock Idiosyncratic Volatility, Firm's Characteristics, and R&D Investments (continued)

	$rdin_{i,t}$	$crd_{i,t}$	$rdin_{i,t}$	$crd_{i,t}$	$rdin_{i,t}$	$crd_{i,t}$	$rdin_{i,t}$	$crd_{i,t}$
$bea_{i,t-1}$	0.506***	0.124***	0.201***	0.125***	0.138***	0.019	0.326***	0.093***
	(37.57)	(5.58)	(18.73)	(5.71)	(5.98)	(0.49)	(23.06)	(3.93)
$yret_{i,t-1}$	-0.049***	0.028***	-0.007***	0.028***	-0.038***	0.032***	-0.059***	0.027***
	(-16.00)	(5.55)	(-3.03)	(5.60)	(-12.54)	(6.49)	(-19.28)	(5.32)
_cons	-0.423***	-0.094***	-0.287***	-0.131***	-0.180***	-0.029	-0.645***	0.043
	(-26.03)	(-3.50)	(-22.24)	(-4.97)	(-9.60)	(-0.93)	(-17.01)	(0.68)
N	78126	78126	78126	78126	78126	78126	78126	78126
R^2	0.3088	0.0134	0.5494	0.0146	0.3117	0.0132	0.3213	0.0135

Notes: This table presents the results from the regression model 2. $Vol_{i,t-1}$ is a firm's idiosyncratic volatility in year t-1. $rdin_{i,t}$ is the ratio of R&D investments to replacement costs. $crd_{i,t}$ is the change in R&D investments to replacement costs at the previous year. MB is the ratio of firm's size to its book equity, RDAT is the ratio of R&D investments to total assets, bea is the ratio of firm's equity to total assets, and lsize is log of a firm's market capitalization. Other control variables are defined in the appendix. The standard errors are clustered at the firm-level, and t-statistics are reported in parentheses. *** (**) (*) indicates significance at the 1%, (5%), (10%) two-tailed level.

In contrast to the effect of firm characteristics on the relation between uncertainty and the change in capital investments, the effects of these firm characteristics on the relation between firm's uncertainty and R&D investment policies are more pronounced and significant. As shown in table 24, less innovative firms or firms with high equity financing will invest more in R&D than other firms when their uncertainty is high. The t-statistic of the coefficient of the interaction of R&D investments and firm idiosyncratic volatility is -10.15, while the t-statistic of the coefficient of the interaction of equity financing and uncertainty is 2.68. This implies that these firms increase their R&D investments if their uncertainty increases. Similarly, large firms tend to invest more in R&D when they face high uncertainty. The t-statistic of the coefficient of the interaction of firm size and idiosyncratic volatility is 8.33. These results show that the incentives to maintain and enhance a firm's competitive advantages are important forces for corporate investment policies under uncertainty.

2.7 Uncertainty, Investment Policies and Industries

An additional way of examining whether the positive relation between uncertainty and R&D investments is caused by the incentives to maintain and enhance a firm's competitive advantage is to compare this relation among firms in different industries with different levels of innovation or of competition. In this section, I compare the effects of idiosyncratic volatility on corporate investments for firms in high tech with firms in non-high tech industries and for firms in more competitive with firms in less competitive industries. I expect that these effects are more pronounced for firms in non-high tech industries and for firms in more competitive industries.

2.7.1 High-tech Industries

I follow Fama and French (1997) to define high tech industries as industries with the following four-digit SIC codes from 3570 to 3579, 3600 to 3629, 3640 to 3646, 3648 to 3649, 3660 to 3692, 3695 to 3699, 4800 to 4899, 7370 to 7373 and 7375. Because firms in high tech industries invest much more in R&D than firms in non-high tech industries, the relation between idiosyncratic volatility and R&D investment proportion will be more pronounced for firms in high tech industries. Therefore, this section will focus on how firms change their corporate investment policies when their uncertainty is high.

Table 25 shows the effects of firms in different industries on the relation between firms' idiosyncratic volatility and their investment policies. As expected, R&D investment proportion will be high for the firms in high tech industries. Thus, firms' idiosyncratic volatility should be significantly positively related to this ratio for these firms. In contrast, capital investments of these firms are usually less than those of the firms in non-high tech industries. As a result, these firms' idiosyncratic volatility is negatively correlated with capital investments.

Because the corporate investment policies for these types of firms are different, I focus on the difference in the change in corporate investment decisions among the firms in different industry groups. Model 3 (column 3) shows that the negative relation between firm uncertainty and the change in its capital investments is more pronounced for the firms in high tech industries. This means that these firms will reduce capital expenditures more when their idiosyncratic volatilities are high than firms in non-high tech do. Interestingly, the results in model 5 (column 5) show that firms in non-high tech industries tend to increase their investments in R&D when their idiosyncratic volatility is

higher than firms in high tech industries. These results are consistent with my hypothesis that firms in less innovative industries tend to invest more in R&D when their uncertainty is high.

Table 25: Stock Idiosyncratic Volatility, High-tech Industries, and Corporate Investments

	$Rd/(cap+rd)_{i,t}$	$invest_{i,t}$	$cinvest_{i,t}$	$rdin_{i,t}$	$crd_{i,t}$
$vol_{i,t-1}$	2.084***	-0.883***	0.004	5.604***	1.161***
	(33.77)	(-15.48)	(0.02)	(36.92)	(4.57)
$Vol*tech_{i,t-1}$	5.228***	0.030	-0.931***	4.875***	-0.406*
	(98.62)	(0.60)	(-6.74)	(37.25)	(-1.85)
$logq_{i,t-1}$	0.072***	0.089***	0.067***	0.264***	0.064***
	(79.74)	(107.48)	(28.58)	(118.66)	(17.41)
$logk_{i,t-1}$	0.003***	-0.004***	-0.012***	-0.001	0.002
	(4.36)	(-7.57)	(-7.93)	(-0.85)	(0.98)
$cfkl_{i,t-1}$	-0.005***	0.003***	-0.000	-0.024***	0.017***
	(-21.29)	(14.46)	(-0.08)	(-42.94)	(17.95)
$bea_{i,t-1}$	0.254***	-0.006	-0.044***	0.435***	0.110***
	(47.41)	(-1.14)	(-3.20)	(33.06)	(5.02)
$yret_{i,t-1}$	-0.034***	0.033***	0.059***	-0.044***	0.031***
	(-28.11)	(29.59)	(18.74)	(-14.55)	(6.26)
N	77,670	78,126	78,126	78,126	78,126
R^2	0.3125	0.2251	0.0283	0.3160	0.0132

Notes: This table reports the results from the regression model 2. $Rd/(cap+rd)_{i,t}$ is the ratio of R&D investments to total investments. $Invest_{i,t}$ is the capital investment ratio which is the value of capital expenditures to replacement costs and $cinvest_{i,t}$ is the change in capital investment to replacement costs at the previous year. $rdin_{i,t}$ is the ratio of R&D investments to replacement costs and $crd_{i,t}$ is the change in R&D investments to replacement costs at the previous year. $Vol_{i,t-1}$ is a firm's idiosyncratic volatility in year t-1. Tech is a dummy variable which is equal to 1 if a firm in high tech industries and 0 otherwise. logq is log of Tobin's Q, cfkl is the ratio of operating income to cost of capital, bea is the book equity ratio, and yret is yearly stock returns. The standard errors are clustered at the firm-level, and t-statistics are reported in parentheses. *** (**) (*) indicates significance at the 1%, (5%), (10%) two-tailed level.

2.7.2 Product Market Competition

Another important way to test my hypothesis that the incentives to maintain a firm's competitive advantage drive its investment policies under an uncertain environment is to examine the effects of market competition on the relationship between firms' uncertainty and their investment policies. Because firms in more competitive industries have higher

pressure on their survivals when they face high specific risk, the effects of idiosyncratic volatility on R&D investment proportion should be more pronounced for these firms.

I measure industry concentration using the Herfindahl index, which is defined as

$$\mathrm{HHI(Sale)}_j = \sum_{i=1}^{I} s_{ij}^2$$

where s_{ij} is the proportion of sales of firm i in industry j, and I is the number of firms in industry j. I calculated this variable each year for each industry using three-digit SIC codes, and then averaged these values over the prior three years. This method helps reduce some potential data errors (Hou (2006)).

Because the HHI measure uses the entire distribution of industry sales information, it reflects the complete picture of industry concentration. A large value for this index implies that the market is concentrated by a small group of firms, while a small value implies that the market is shared by many competing firms.

Some other common ways to measure the HHI are to use market capitalization or total assets to calculate market share. Because these measures are highly correlated with each other, I focus on HHI index calculated by sales. The results are consistent when I use this index measured by total assets or market capitalization.

Table 26 reports the effects of industry competition on the relationship between firms' idiosyncratic volatility and their investment decisions. As expected, firms in more concentrated industries tend to invest less in R&D than in capital expenditures. Moreover, when firm's uncertainty increases, these firms invest less in R&D. In contrast,

these firms invest more in capital than firms in more competitive industries when firms' idiosyncratic volatility is high.

Table 26: Stock Idiosyncratic Volatility, Product Market Competition, and Corporate Investments

	$Rd/(cap+rd)_{i,t}$	$invest_{i,t}$	$cinvest_{i,t}$	$rdin_{i,t}$	$crd_{i,t}$
$vol_{i,t-1}$	5.048***	-1.243***	-0.557***	8.687***	1.223***
	(61.53)	(-17.16)	(-2.74)	(45.14)	(4.64)
$Vol*hhi_{i,t-1}$	-3.360***	1.084***	0.653	-6.783***	-1.003**
	(-16.50)	(6.05)	(1.30)	(-14.27)	(-2.11)
$hhi_{i,t-1}$	-0.110***	-0.084***	-0.012	-0.264***	
	(-12.75)	(-11.09)	(-0.54)	(-13.05)	
$logq_{i,t-1}$	0.080***	0.088***	0.065***	0.264***	0.063***
	(84.88)	(106.86)	(27.85)	(119.74)	(17.07)
$logk_{i,t-1}$	0.004***	-0.005***	-0.013***	-0.002	0.002
	(6.49)	(-8.22)	(-8.10)	(-1.52)	(0.94)
$cfkl_{i,t-1}$	-0.004***	0.003***	-0.000	-0.024***	0.017***
	(-18.54)	(14.43)	(-0.15)	(-41.85)	(18.01)
$bea_{i,t-1}$	0.283***	-0.009*	-0.051***	0.443***	0.105***
	(50.63)	(-1.74)	(-3.71)	(33.88)	(4.79)
$yret_{i,t-1}$	-0.035***	0.034***	0.059***	-0.043***	0.031***
	(-27.85)	(29.95)	(18.84)	(-14.41)	(6.31)
N	77,670	78,126	78,126	78,126	78,126
R^2	0.2466	0.2263	0.0278	0.3223	0.0132

Notes: This table presents the results from the regression model 2. $Rd/(cap+rd)_{i,t}$ is the ratio of R&D investments to total investments. $Invest_{i,t}$ is the capital investment ratio which is the value of capital expenditures to replacement costs and $cinvest_{i,t}$ is the change in capital investment to replacement costs at the previous year. $rdin_{i,t}$ is the ratio of R&D investments to replacement costs and $crd_{i,t}$ is the change in R&D investments to replacement costs at the previous year. $Vol_{i,t-1}$ is a firm's idiosyncratic volatility in year t-1. HHI the Herfindahl index. logq is log of Tobin's Q, cfkl is the ratio of operating income to cost of capital, bea is the book equity ratio, and yret is yearly stock returns. The standard errors are clustered at the firm-level, and t-statistics are reported in parentheses. *** (**) (*) indicates significance at the 1%, (5%), (10%) two-tailed level.

The results in table 26 support my hypothesis that firms in more competitive industries tend to invest more in R&D than firms in less competitive industries do. This implies that

the incentives to maintain a firm's competitive advantage are important drivers of the relation between idiosyncratic volatility and corporate investment policies.

2.8 R&D Investments and Firms' Idiosyncratic Volatility in the Future

The previous sections document that that firms prefer R&D investments when they face high uncertainty in their investment opportunities. In this section, I will focus on the benefits of R&D investments which can drive the relation between idiosyncratic volatility and corporate investment decisions.

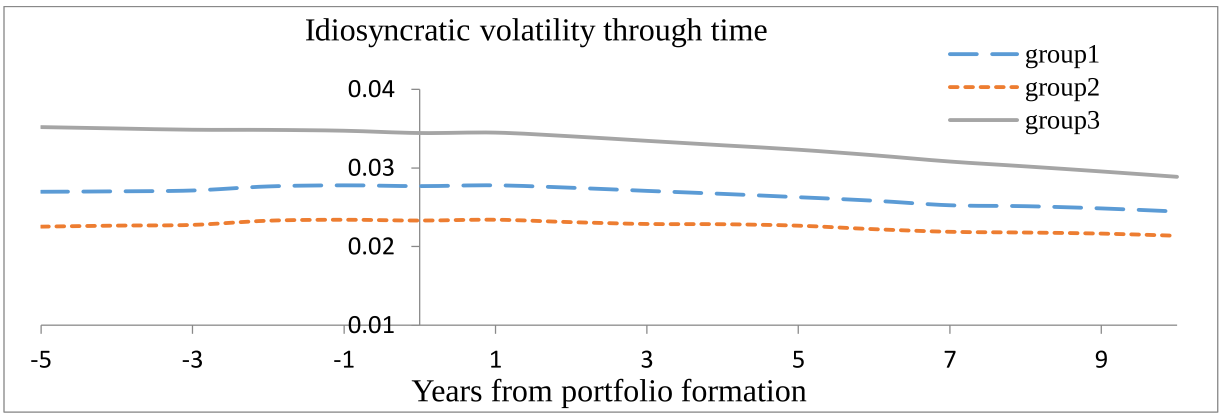
As shown in the recent literature (e.g. Eberhart et al. (2004), Eberhart et al. (2008), and Lin (2012)), R&D investments will usually generate more growth opportunities and improve a firm's productivity. Eberhart et al. (2004) find that firms experience significantly positive long term abnormal operating performance following an increase in their R&D investments. Moreover, Eberhart et al. (2008) document that R&D investments will benefit bondholders because the significant increase in operating performance more than offsets the increase in the firm's default risk. In addition, Lin (2012) suggests that R&D investments will improve a firm's productivity.

This section will present another benefit of R&D investments. I document that an increase in R&D investments will reduce a firm's uncertainty in the future. This evidence is also consistent with the benefits of R&D investments shown in the literature. In addition, it supports my hypothesis that firms that face high uncertainty tend to invest more in R&D to reduce specific risk and improve competitive advantage in the future.

I sort all firms by year into three groups based on their R&D intensity captured by R&D expenditures to replacement costs. Group 1 consists of firms with R&D investments less

than the 33rd percentile while group 3 includes firms with R&D investments more than the 66th percentile. The median R&D investments of firms in each group are shown in figure 3. This figure shows that while firms with high R&D investments (group 3) have higher idiosyncratic volatilities than firms in the other groups, these volatilities tend to reduce over time after portfolio formation. This implies that R&D investments can reduce a firm's idiosyncratic volatility. This pattern is consistent when R&D intensity is measured by R&D investments to total assets or R&D to sales (not reported) as well as when firms without R&D are excluded.

Figure 3: Firms' Idiosyncratic Volatilities following Their R&D Investments



Notes: This figure shows the median firm's stock return idiosyncratic volatility following its R&D investments. Every year, I sort all firms into three groups based on their R&D intensity captured by R&D expenditures to replacement costs. Group 1 consists of firms with R&D investments less than 33rd percentile while group 5 includes firms with R&D investments more than 66th percentile.

Table 27 reports the results from the regression of changes in future idiosyncratic volatilities on changes in R&D investments and other firm's characteristics. These results show that an increase in R&D (capital) investments will reduce (raise) a firm's idiosyncratic volatility in the next several years. T-statistics of the coefficients of change

in R&D investments are less than -2.70. These results suggest that firms with high uncertainty should invest more in R&D to improve their competitive advantage.

Table 27: Change in R&D Investments and Future Idiosyncratic Volatility

	$cvol_{i,(t+1)-t}$	$cvol_{i,(t+2)-t}$	$cvol_{i,(t+3)-t}$	$cvol_{i,(t+4)-t}$
$crd_{i,t}$	-0.000***	-0.000***	-0.001***	-0.000***
	(-6.30)	(-7.15)	(-5.53)	(-2.74)
$cinvest_{i,t}$	0.000***	0.000***	0.001***	0.001***
	(4.89)	(6.27)	(9.98)	(5.66)
$vol_{i,t}$	-0.319***	-0.418***	-0.507***	-0.575***
	(-107.87)	(-105.63)	(-107.90)	(-110.23)
$logq_{i,t}$	-0.001***	-0.001***	-0.001***	-0.001***
	(-26.40)	(-19.07)	(-17.41)	(-16.58)
$logk_{i,t}$	-0.002***	-0.003***	-0.003***	-0.003***
	(-67.66)	(-66.29)	(-66.21)	(-65.35)
$cfkl_{i,t}$	-0.000***	-0.000***	-0.000***	-0.000***
	(-15.69)	(-13.83)	(-11.89)	(-9.77)
$be_{i,t}$	-0.006***	-0.007***	-0.007***	-0.006***
	(-22.20)	(-19.32)	(-16.17)	(-13.39)
$yret_{i,t}$	-0.002***	-0.002***	-0.002***	-0.001***
	(-35.66)	(-25.36)	(-15.40)	(-13.08)
_cons	0.006***	0.009***	0.010***	0.009***
	(16.62)	(19.68)	(20.77)	(16.34)
N	90,135	80,935	72226	64,405
R^2	0.1967	0.2239	0.2451	0.2723

Notes: This table reports the effects of change in R&D investments on the change in a firm's idiosyncratic volatilities in future. $cvol_{i,(t+k)-t}$ is the change in the idiosyncratic volatility of firm i from year t to year t+k. $crd_{i,t}$ is the change in R&D investments to replacement costs at the previous year and $cinvest_{i,t}$ is the change in capital investment to replacement costs at the previous year. logq is log of Tobin's Q, cfkl is the ratio of operating income to cost of capital, bea is the book equity ratio, and yret is yearly stock returns. The standard errors are clustered at the firm-level, and t-statistics are reported in parentheses. *** (**) (*) indicates significance at the 1%, (5%), (10%) two-tailed level.

2.9 Robustness Tests

In previous sections, I measure the R&D investments by the ratio of a firm's R&D expenditures to its replacement costs. However, the current literature (e.g. Chan et al. (2001), Eberhart et al. (2004), and Eberhart et al. (2008)) usually measures the R&D

investment ratio by the ratios of R&D to sales or R&D to assets. Moreover, Eberhart et al. (2008) suggest that these R&D intensity measures are better than the ratio of R&D to the market value of equity. Thus, in this section I will use these R&D investment measures and examine the effects of firm's idiosyncratic volatility on these R&D measures.

Another reason to use different measures of R&D investments is to avoid endogeneity problems in empirical corporate finance (Roberts and Whited (2012)). Because there are no perfect measure investment opportunities, potential endogeneity biases may lead to the wrong conclusion. Thus, using different measures of R&D investments helps me reduce bias when I estimate the regression model.

Table 28: Stock Idiosyncratic Volatility, and R&D Investments

	$rdat_{i,t}$	$rdsale_{i,t}$	$crdat_{i,t}$	$crdsale_{i,t}$
$vol_{i,t-1}$	1.597***	52.582***	0.008	9.783***
	(75.02)	(6.56)	(0.64)	(3.30)
$logq_{i,t-1}$	0.023***	0.628***	0.004***	0.105**
	(70.70)	(5.06)	(20.47)	(2.29)
$logk_{i,t-1}$	0.004***	0.202**	0.001***	0.048
	(19.21)	(2.41)	(3.88)	(1.55)
$cfkl_{i,t-1}$	-0.003***	-0.175***	0.000***	-0.009
	(-29.69)	(-5.46)	(7.54)	(-0.74)
$bea_{i,t-1}$	0.071***	2.563***	0.014***	0.657**
	(35.83)	(3.46)	(11.61)	(2.40)
$yret_{i,t-1}$	-0.004***	-0.246	0.005***	0.020
	(-8.03)	(-1.46)	(17.10)	(0.31)
_cons	-0.049***	-2.193**	-0.004***	-0.491
	(-20.49)	(-2.46)	(-3.04)	(-1.49)
N	78,126	78,126	78,126	78,126
R^2	0.13220	0.0015	0.0200	0.0005

Notes: This table reports the results from the regression model 2 using different measures to proxy for R&D investments. $rdat_{i,t}$ is the ratio of R&D investments to total assets and $rdsale_{i,t}$ is the ratio of R&D investments to total sales. $crdat_{i,t}$ is the change in R&D investment to total assets at the previous year and $crdsale_{i,t}$ is the change in R&D investments to total sales in previous year. $Vol_{i,t-1}$ is a firm's idiosyncratic volatility in year t-1. logq is log of Tobin's Q, cfkl is the ratio of operating income to cost of capital, bea is the book equity ratio, and yret is yearly stock returns. The standard errors are clustered at the firm-level, and t-statistics are reported in parentheses. *** (**) (*) indicates significance at the 1%, (5%), (10%) two-tailed level.

Using the simultaneous equation estimation method, I investigate the effects of a firm's idiosyncratic volatility on its R&D investments captured by the ratios of R&D to sales and to total assets. The results are shown in table 28. Consistent with the previous conclusion about the positive relation between uncertainty and R&D investment, these results show that firms with high idiosyncratic volatility will invest more in R&D. The t-statistics of coefficients of idiosyncratic volatilities in model 1 (column 1) and 2 (column 2) are greater than 6. Moreover, idiosyncratic volatility is significantly correlated with the change in R&D investments measured by the ratio of R&D to sales.

As documented in literature (e.g. Pastor and Veronnesi (2006 and 2009)), firms in high tech industries tend to have higher specific volatility. Thus, the positive relation between a firm's idiosyncratic risk and R&D investments may depend on the firms in these industries. To eliminate this possible explanation, I will exclude the firms in high tech industries and examine the effects of firm's idiosyncratic volatility on its investment policies.

Table 29 shows the results of the regression of firm's investments on its idiosyncratic volatility and other characteristics for non-high tech firms. Consistent with the previous results, table 29 presents that firms tend to invest more in R&D when their specific risk is high. The t-statistics of this coefficient are larger than 10 which are much larger than these statistics in tables 20, 21 and 24. Together with the previous results, this evidence shows that less innovative firms tend to invest more in R&D when their uncertainty is high in order to maintain and enhance their competitive advantage.

Table 29: Stock Idiosyncratic Volatility and Corporate Investments for Firms in Non- high tech Industries

	$Rd/(cap+rd)_{i,t}$	$Rd/(cap+rd)_{i,t}$	$invest_{i,t}$	$invest_{i,t}$	$rdin_{i,t}$	$rdin_{i,t}$
$Vol_{i,t-1}$	2.997***		-0.798***		7.300***	
	(45.22)		(-12.95)		(46.71)	
$Cvol_{i,t-1}$		1.003***		-1.040***		0.847***
		(12.77)		(-14.40)		(4.58)
$logq_{i,t-1}$	0.078***	0.067***	0.080***	0.082***	0.228***	0.200***
	(79.09)	(70.19)	(86.92)	(92.34)	(97.86)	(88.47)
$logk_{i,t-1}$	0.007***	-0.009***	-0.007***	-0.003***	0.011***	-0.030***
	(11.15)	(-16.20)	(-11.93)	(-6.40)	(6.81)	(-22.71)
$cfkl_{i,t-1}$	-0.006***	-0.007***	0.003***	0.003***	-0.031***	-0.033***
	(-25.45)	(-29.09)	(13.21)	(14.11)	(-51.31)	(-55.17)
$bea_{i,t-1}$	0.202***	0.179***	-0.009	-0.004	0.421***	0.360***
	(34.52)	(30.51)	(-1.57)	(-0.76)	(30.35)	(25.95)
$yret_{i,t-1}$	-0.032***	-0.024***	0.037***	0.034***	-0.044***	-0.026***
	(-21.48)	(-16.18)	(27.07)	(25.22)	(-12.54)	(-7.46)
_cons	-0.043***	0.010	0.189***	0.174***	-0.331***	-0.204***
	(-6.44)	(1.49)	(30.11)	(28.09)	(-20.73)	(-12.89)
N	58,283	58,283	58,683	58,683	58,683	58,683
R^2	0.1832	0.1828	0.2116	0.2116	0.2670	0.2667

Notes: This table shows the results from the regression model 2 for firms in non-high tech industries. $Rd/(cap+rd)_{i,t}$ is the ratio of R&D investments to total investments. $Invest_{i,t}$ is the capital investment ratio which is the value of capital expenditures to replacement costs and $rdin_{i,t}$ is the ratio of R&D investments to replacement costs. $Vol_{i,t-1}$ is a firm's idiosyncratic volatility in year t-1. $Cvol_{i,t-1}$ is the change in idiosyncratic volatility for firm i from year t-2 to t-1. logq is log of Tobin's Q, cfkl is the ratio of operating income to cost of capital, bea is the book equity ratio, and yret is yearly stock returns. The standard errors are clustered at the firm-level, and t-statistics are reported in parentheses. *** (**) (*) indicates significance at the 1%, (5%), (10%) two-tailed level.

2.10 Conclusion

This essay examines the effects of a firm's idiosyncratic volatility on its investment policies. While the negative relation between a firm's idiosyncratic volatility and its capital investments is largely documented in the literature on irreversible investments and real options (e.g. Pindyck (1991), and Dixit and Pindyck (1994)), and on managerial risk aversion behavior (Panousi and Papanikolaou (2012)), the effects of a firm's uncertainty on its R&D investments are widely neglected (e.g. Bloom (2007)).

Using the idiosyncratic volatility of stock returns to proxy for uncertainty, I find that a firm usually invests more in R&D when uncertainty is high. As a result, a firm's R&D investment proportion is significantly correlated with its idiosyncratic volatility. I further hypothesize that the positive relation between a firm's uncertainty and its R&D investments is caused by the incentives to maintain and enhance its competitive advantage. As documented in the literature (e.g. Eberhart et al. (2004), and Lin (2012)), R&D investments usually result in new technological progress and typically increase the productivity of the firm's physical investments. This investment also generates more growth opportunities and will bring long-term benefits to a firm. Beyond these benefits, I document that an increase in R&D investments will also reduce a firm's idiosyncratic risk in subsequent years following its investments. My results are consistent with the strategic growth option framework.

I also find that this positive relation is more pronounced for firms with the high incentives to maintain and enhance its competitive advantage; such as less innovative firms or firms in more competitive industries. I further document that large firms who are less innovative (e.g. Seru (2010), and Phillips and Zhdanow (2012)) will invest more in

R&D when their idiosyncratic volatility is high. Finally, my evidence shows that these incentives, which are neglected in the current literature on the effects of uncertainty on corporate investments, are important forces scholars must examine in order to better understand a firm's investment policies under uncertainty.

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