Journal of
*Risk and Financial Management*

MDPI

*Article*

# Innovation Output and Idiosyncratic Volatility: US Evidence

**Naji Mohammad Alshammasi [1,2,*] and Adel Abdulkarim Almomen [3]**

[1] Department of Accounting and Finance, KFUPM Business School, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
[2] Capital Market Authority, Riyadh 11642, Saudi Arabia
[3] Department of Finance, College of Business Administration, Prince Sultan University, Riyadh 12345, Saudi Arabia
* Correspondence: nshammasi@kfupm.edu.sa

**Abstract:** Firms engaging in innovative practices have patents to prevent competitive forces from eroding the resulting economic rents; however, there is limited evidence regarding the impact of innovation on risk. We shed new light on how firms' involvement in innovation activities impacts their volatility, particularly their idiosyncratic volatility. In this paper, we empirically examine the effect of innovation on idiosyncratic volatility. To do so, we empirically examine the impact of innovation, measured by patents weighted by citations and R&D expenditure, on the idiosyncratic volatility of firms. Using a large sample of 8256 US firms, we find that more innovation is associated with lower idiosyncratic volatility. We also find that information uncertainty is the channel through which innovation affects idiosyncratic risk. The results are robust for different measures of idiosyncratic volatility. These results have empirical implications for investors, managers, and firms engaging in innovation-related activities.

**Keywords:** innovation; patents; citations; idiosyncratic volatility; information uncertainty

**JEL Classification:** D8; G12; G14; O33

check for updates

**Citation:** Alshammasi, Naji Mohammad, and Adel Abdulkarim Almomen. 2023. Innovation Output and Idiosyncratic Volatility: US Evidence. *Journal of Risk and Financial Management* 16: 24. https://doi.org/10.3390/jrfm16010024

Academic Editor: Yenchun Jim Wu

Received: 5 November 2022
Revised: 30 November 2022
Accepted: 7 December 2022
Published: 30 December 2022



## 1. Introduction

The purpose of this paper is to investigate the impact of innovation output on idiosyncratic volatility (*IVOL*). Economic theory suggests that innovation contributes positively to firm value and economic growth (Jaffe 1986; Hall 1993; Solow 1957). On the other hand, innovation can also have a "creative destruction" impact on markets. Shiller (2000) suggests that excess volatility increases significantly in periods of rapid technological innovation. An analysis of trends in unsystematic risk shows that it has increased since the 1960s, and this might be attributed to new technologies and listing of riskier companies (Brown and Kapadia 2007).

Firms engage in innovative activities, at first, through investing in R&D projects that are inherently risky due to their low success rate, irreversibility, and high adjustment costs (Holmstrom 1989; Bloom 2007). These investments increase the uncertainty of future economic growth and lead to an increase in stock return volatility (Chan et al. 2001; Kung and Schmid 2015). If R&D projects produce valuable innovations, firms are more likely to apply for patents to secure the economic rent resulting from these projects. A patent provides legal protection for firms and reduces the uncertainty surrounding future cash flows (Balasubramanian and Sivadasan 2011; Hall et al. 2005; Kogan et al. 2017). In addition, applications provide significant details about the invention. Thus, obtaining patents is expected to help reduce the uncertainty associated with R&D projects.

Previous studies have investigated the impact of innovation on firms' risk levels. Several studies have shown that innovation increases firms' risk levels (Chan et al. 2001; Zhang 2015; Gu 2016). On the other hand, other studies show that firms' risk levels decrease as a result of innovative activities (Christensen et al. 1998; Cefis and Marsili 2006). In many of these studies, innovation is measured by R&D expenditure. However, R&D expenditure captures the input part of the innovation process that has different dynamics and is expected to have different impacts on firms' risk level when compared with innovation output. Mazzucato and Tancioni (2012) use patents to measure innovation in the pharmaceutical industry. Their results show a positive relationship between innovation and volatility.

In this paper, we argue that R&D expenditure and patents have different impacts on firms' risk, as measured by idiosyncratic volatility. Increasing R&D expenditure increases stock volatility because of the high risk of these projects' outcomes and the uncertainty surrounding future cash flows. However, if these projects are successful and the innovation output is patented, there will be a higher level of certainty regarding future cash flow and, hence, lower risk.

The main prediction of this paper is that innovation output and *IVOL* are negatively correlated after controlling for other relevant factors, such as growth, size, age, and industry competition. In addition, based on the information uncertainty argument, we predict that the negative relationship between innovation output and *IVOL* is stronger for firms with high information uncertainty.

Using a large sample of 8256 US firms from 44 different industries over the 1982 to 2015 period, we use a conventional double sorting approach. We double-sort firms in our sample by patents and R&D expenditure. The tests reveal that, when holding the R&D level constant, the level of *IVOL* decreases monotonically as the number of patents increases across all R&D quantiles. This indicates that R&D and patents capture different dynamics of the innovation process. Additionally, after double-sorting firms in our sample by information uncertainty and patents, we find that the marginal impact of patents increases at higher levels of information uncertainty.

Furthermore, after controlling for the relevant variables, regression analysis indicates that innovation output has a negative impact on *IVOL*. The results are robust to alternative *IVOL* measures and firm and time fixed effects. In addition, we find that the impact of innovation output is more pronounced for firms with higher information uncertainty. The marginal impact of patenting is low on firms with low information uncertainty because patents do not add more information to investors about the firm compared to firms with high information uncertainty.

This paper contributes to the literature on the relationship between innovation and stock price behavior (see, e.g., Cohen et al. 2013; Chambers et al. 2002; Eberhart et al. 2004). The paper adds to the literature regarding innovation and risk by examining the impact of innovation output on *IVOL* over a large sample from different industries. Second, we identify information uncertainty as the channel through which patents reduce *IVOL*. We show that patents have a higher impact, in absolute terms, on firms with higher information uncertainty.

This work is related to the literature on understanding the behavior of *IVOL*. Shleifer and Vishny (1997) suggest that, in the presence of market frictions, *IVOL* may deter arbitrageurs from exploiting mispricing opportunities. This means that mispricing can exist and persist, which directly affects the cost of capital and the allocation of capital within the firm. Additionally, the behavior of *IVOL* affects the number of securities that investors must hold to reach full diversification, and this directly affects the value of the options on individual stocks (Campbell et al. 2001). Moreover, empirical results suggest that *IVOL* is priced in the cross-section of returns (Ang et al. 2006).

The remainder of the article proceeds as follows. Section 2 provides the literature review and develops the hypothesis. Section 3 describes the sample, defines the variables, and presents the summary statistics. Section 4 reports the empirical results. Section 5 concludes the paper.

## 2. Hypothesis Development

Schumpeter (1934) suggests that firms can achieve long-term success by continuous innovation that creates economic rents that establish a temporary monopoly. The process of capturing these economic rents includes spending on R&D projects and protecting fruitful projects through patenting. Empirical evidence suggests that firms that are more innovative, i.e., those that have patents with more citations, have higher market valuations (Hall et al. 2005).

The economic impact of R&D spending and patenting may differ due to the different nature of these activities. R&D spending is an example of Knightian uncertainty because its benefits are largely unknown (Knight 1921). Thus, as a firm increases its R&D expenditure, its risk level is expected to increase. Zhang (2015) shows that R&D investment increases distress risk. In addition, Bloom (2007) suggests that R&D investment is inflexible and has high adjustment costs. Xu (2006) investigates the reaction of stock price volatility to R&D progress. He shows that stock price volatility decreases proportionally with progress in the R&D process. Patents, on the other hand, work in the opposite direction from R&D spending. When a firm successfully patents its innovative activities, the risk associated with R&D spending and innovative activities is reduced, and this is expected to be reflected in the firm's stock price volatility. Based on this discussion, we formulate our first hypothesis:

**Hypothesis 1a.** *IVOL is negatively associated with patents, ceteris paribus.*

Although patents decrease *IVOL*, firms with low information uncertainty would not gain much from patenting their activities because patents do not help market participants to learn more about the future profitability of the firm. In contrast, firms with high information uncertainty are expected to have a higher benefit from their patents because they disseminate information to the market about the future profitability of these firms. As a result, patents should have a higher impact, in absolute terms, on *IVOL* in firms with higher information uncertainty. This discussion leads us to our second hypothesis:

**Hypothesis 1b.** *The effect of patents on IVOL is stronger when firms have higher information uncertainty, ceteris paribus.*

## 3. Sample Selection and Research Design

The sample in this study comprises US firms with available data in CompStat, Center of Research in Security Prices (CRSP), and CRSP/CompStat Merged database from 1982 to 2015. In addition, Fama and French 3-factor and Carhart 4-factor data were obtained from the Fama and French & Liquidity Factors database. The patents dataset is constructed from three databases from the United Patent Trademark Office (USPTO) data. The first database is the National Bureau of Economic Research (NBER)'s Patent Data Project database (PDP). This dataset is constructed by Hall et al. (2001). The second database was built by Kogan et al. (2017). The third database was created by Li et al. (2014), and it is used to update the first two databases.

The choice of 1982 as a starting date for the sample is due to the availability of the data needed to construct all the dependent variables. We exclude firms in the banking, utilities, insurance, and other industries (i.e., Fama and French-48 industry classification (44, 31, 45, and 48, respectively). Additionally, we exclude firms with negative net income. The final sample consists of 8256 firms, representing 79,923 firm years. The choice of 2015 as the end date for the sample was in order to account for the number of patent citations.

Table 1 shows the sample's frequency distribution based on the Frama and French 48-industry classification (Fama and French 1997). The table shows that the sampled firms are classified into 44 industries. The industries with the highest percentage of observations are Business Services (12.1%), Electronic Equipment (8.0%), and Pharmaceutical Products (6.3%).

**Table 1.** Sample distribution of the sample according to the Fama and French 48-industry classification code.

| Fama–French 48-Industry Code | Frequency | % | Cum. Frequency |
|---|---|---|---|
| Agriculture | 321 | 0.4% | 0.4% |
| Food Products | 1687 | 2.1% | 2.5% |
| Candy & Soda | 311 | 0.4% | 2.9% |
| Beer & Liquor | 381 | 0.5% | 3.3% |
| Tobacco Products | 80 | 0.1% | 3.4% |
| Recreation | 707 | 0.9% | 4.3% |
| Entertainment | 1215 | 1.5% | 5.8% |
| Printing and Publishing | 741 | 0.9% | 6.7% |
| Consumer Goods | 1596 | 2.0% | 8.7% |
| Apparel | 1305 | 1.6% | 10.3% |
| Healthcare | 1733 | 2.1% | 12.5% |
| Medical Equipment | 3255 | 4.0% | 16.5% |
| Pharmaceutical Products | 5112 | 6.3% | 22.8% |
| Chemicals | 1773 | 2.2% | 25.0% |
| Rubber and Plastic Products | 818 | 1.0% | 26.1% |
| Textiles | 463 | 0.6% | 26.6% |
| Construction Materials | 1855 | 2.3% | 28.9% |
| Construction | 672 | 0.8% | 29.8% |
| Steel Works, Etc. | 1326 | 1.6% | 31.4% |
| Fabricated Products | 345 | 0.4% | 31.8% |
| Machinery | 3432 | 4.3% | 36.1% |
| Electrical Equipment | 1630 | 2.0% | 38.1% |
| Automobiles and Trucks | 1342 | 1.7% | 39.8% |
| Aircraft | 399 | 0.5% | 40.3% |
| Shipbuilding, Railroad Equipment | 153 | 0.2% | 40.4% |
| Defense | 173 | 0.2% | 40.7% |
| Precious Metals | 808 | 1.0% | 41.7% |
| Non-Metallic and Industrial Metal Mining | 542 | 0.7% | 42.3% |
| Coal | 153 | 0.2% | 42.5% |
| Petroleum and Natural Gas | 4394 | 5.4% | 48.0% |
| Communication | 2662 | 3.3% | 51.3% |
| Personal Services | 890 | 1.1% | 52.4% |
| Business Services | 9766 | 12.1% | 64.5% |
| Computers | 3916 | 4.9% | 69.3% |
| Electronic Equipment | 6433 | 8.0% | 77.3% |
| Measuring and Control Equipment | 2253 | 2.8% | 80.1% |
| Business Supplies | 1339 | 1.7% | 81.7% |
| Shipping Containers | 250 | 0.3% | 82.0% |
| Transportation | 2805 | 3.5% | 85.5% |
| Wholesale | 3303 | 4.1% | 89.6% |

**Table 1.** *Cont.*

| Fama–French 48-Industry Code | Frequency | % | Cum. Frequency |
|---|---|---|---|
| Retail | 4706 | 5.8% | 95.4% |
| Restaurants, Hotels, Motels | 1784 | 2.2% | 97.6% |
| Real Estate | 532 | 0.7% | 98.3% |
| Trading | 1372 | 1.7% | 100.0% |
| Total | 80,733 | 100.0% | |

Table 2 shows the summary statistics of the dependent and control variables. To minimize the impact of outliers, all variables are winsorized at the 1st and 99th percentiles. The annualized standard deviation of the residuals of the market model using weekly data ($IVOL\_MM$) is 0.53 over the sample period (the standard deviation of the residuals of the Fama and French three-factor model using weekly data ($IVOL\_FF3$) and the standard deviation of the residuals of the Carhart four-factor model using weekly data ($IVOL\_C4$) are also reported).

**Table 2.** Summary statistics of variables used in the analysis. Variables' definitions are provided in Appendix A.

| | N | Mean | S. D. | p25 | Median | p75 | Min | Max |
|---|---|---|---|---|---|---|---|---|
| $IVOL\_MM_{it}$ | 77,923 | 0.530 | 0.357 | 0.302 | 0.444 | 0.644 | 0.131 | 2.460 |
| $IVOL\_FF3_{it}$ | 77,923 | 0.507 | 0.342 | 0.288 | 0.424 | 0.618 | 0.125 | 2.344 |
| $IVOL\_C4_{it}$ | 77,923 | 0.498 | 0.336 | 0.283 | 0.416 | 0.607 | 0.122 | 2.306 |
| $PAT_{it}$ | 77,923 | 0.222 | 0.580 | 0 | 0 | 0.122 | 0 | 3.474 |
| $R\&D_{it}$ | 77,923 | 0.176 | 0.859 | 0 | 0.001 | 0.063 | 0 | 7.384 |
| $DISP_{it}$ | 43,827 | 0.118 | 0.169 | 0.028 | 0.057 | 0.130 | 0.001 | 1.070 |
| $CFVOL_{it}$ | 77,923 | 0.131 | 0.120 | 0.054 | 0.093 | 0.164 | 0.013 | 0.672 |
| $SIZE_{it}$ | 77,923 | 5.449 | 2.291 | 3.729 | 5.326 | 7.026 | 0.808 | 11.111 |
| $AGE_{it}$ | 77,923 | 2.746 | 0.678 | 2.197 | 2.708 | 3.258 | 1.609 | 4.344 |
| $MB_{it}$ | 77,923 | 2.801 | 3.232 | 1.093 | 1.821 | 3.150 | 0.175 | 21.60 |
| $LEV_{it}$ | 77,923 | 0.341 | 0.228 | 0.152 | 0.303 | 0.496 | 0.015 | 0.912 |
| $CASH_{it}$ | 77,923 | 0.177 | 0.201 | 0.028 | 0.098 | 0.258 | 0 | 0.868 |
| $DPO_{it}$ | 77,923 | 0.159 | 0.382 | 0 | 0.015 | 0.204 | −0.973 | 2.284 |
| $BIDASK_{it}$ | 77,923 | 0.031 | 0.043 | 0.003 | 0.015 | 0.039 | 0 | 0.241 |
| $ROA_{it}$ | 77,923 | 0.079 | 0.176 | 0.045 | 0.111 | 0.168 | −0.768 | 0.389 |
| $HHI_{it}$ | 77,923 | 0.068 | 0.045 | 0.038 | 0.054 | 0.077 | 0.025 | 0.259 |
| $TANG_{it}$ | 77,923 | 0.285 | 0.234 | 0.097 | 0.215 | 0.415 | 0.006 | 0.903 |

The average firm in our sample has weighted patents (*PAT*) of 0.22 and an R&D expense as a percentage of sales (R&D) of 0.18. On average, the standard deviation of analysts' expectations of a firm's EPS scaled by price (*DISP*) is 0.18, the cash flow volatility (*CFVOL*) is 0.13, the firm size (*SIZE*) is 5.43, a natural log of age *(AGE)* of 2.74, a market to book ratio (*M.B.*) of 2.80, and a market leverage ratio (*LEV*) of 0.34. The average cash holding included in our sample (*CASH*) is 0.18. The average firm has an average dividend payout ratio *(DPO)* of 0.16, a bid–ask spread (*BIDASK*) of 0.03, and an ROA of 0.08. Additionally, the average concentration within an industry *(HHI)* and tangibility of assets (*TANG*) are 0.07 and 0.29, respectively.

To investigate the impact of innovation on *IVOL*, we estimate the following panel regression model:

$$IVOL_{it} = \alpha + \beta_1 PAT_{it-1} + \beta' \times Controls_{it-1} + Firm_i + Year_t + \varepsilon_{it} \quad (1)$$

The dependent variable in the model is *IVOL* at time t. The primary variable of interest is $PAT_{it-1}$. The coefficient of the variable is expected to be negative and significant. $Controls_{it-1}$, as discussed previously, is a vector of firm characteristics that could affect the *IVOL*. $Firm_i$ and $Year_t$ are firm and year dummies that are available in the model to control for firm and time fixed effects. We acknowledge that a firm's innovative activities and other included financial variables are contemporaneously determined within the firm. Thus, we follow Mazzucato and Tancioni (2012) and use the lagged values of the control variables. This means that pre-determined values are used to estimate simultaneous relations.

To test H1b, we estimate the following panel regression model:

$$IVOL_{it} = \alpha + \beta_1 PAT_{it-1} + \beta_2 PAT_{it-1} \times DISP_{it-1} + \beta' \times Controls_{it-1} + Firm_i + Year_t + \varepsilon_{it} \quad (2)$$

In this model, we interact the *PAT* with *DISP* to investigate the marginal impact of innovation output on firms with different levels of information uncertainty. We expect the coefficient on the interaction variable to be negative and statistically significant.

*Variables' Definitions*

To estimate *IVOL*, we use the annualized standard deviation of the residuals of the market model. The model is estimated using the following regression equation:

$$r_{it} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \quad (3)$$

where $r_{it}$ is the excess return for stock $i$ at time $t$, and $R_{m,t}$ is the value-weighted excess market return at time $t$. The model is estimated using weekly returns. We require at least 6 weeks to compute the *IVOL*. The *IVOL* that is calculated from the market model is denoted $IVOL\_MM$.

Additionally, we employ the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. All the models are estimated using weekly returns. We require at least six observations to compute the *IVOL*. The Fama and French three-factor model is calculated using the following regression equation:

$$r_{it} = \alpha_i + b_i R_{m,t} + s_i SMB_{i,t} + h_t HML_{i,t} + \varepsilon_{i,t} \quad (4)$$

where $SMB_{i,t}$ and $HML_{i,t}$ are the size premium (small minus big) and the value premium (high minus low). The Carhart four-factor model is estimated using the following regression model:

$$r_{it} = \alpha_i + b_i R_{m,t} + s_i SMB_{i,t} + h_t HML_{i,t} + u_i UMD_{i,t} + \varepsilon_{i,t} \quad (5)$$

where $UMD_{i,t}$ is the momentum premium (up minus down). The *IVOL* values that are computed from the Fama and French three-factor model and the Carhart four-factor model are denoted $IVOL\_FF3$ and $IVOL\_C4$, respectively.

Two variables are used in the literature to measure a firm's innovation: R&D expenditure and number of patents. The former only captures an observable input of innovation rather than the quality of innovation. However, the latter measure captures the firm's utilization of observable and unobservable innovation inputs and turning them into outputs. For innovation, we use the natural log of the number of patents weighted by citations *(PAT)* to capture a firm's innovation output. Following He and Tian (2013) and Fang et al. (2014), we use the natural log of one plus. The number of patents weighted by citations as a measure of corporate innovation output is used to avoid losing observations from the sample.

To address truncation bias, we follow Squicciarini et al. (2013) and count citations over seven years after the publication date. Thus, most patents have the same window of time to be cited regardless of their application year. Moreover, we follow Atanassov (2013) and drop the last two years of the sample because they exhibit severe forms of bias.

We control for several variables that have been shown to affect *IVOL*. We control for operations risk using the standard deviation of the operating cash flow over the last three years (Zhang 2006). Cao et al. (2008) show that growth opportunities positively correlate to *IVOL*. Thus, we include the market-to-book ratio (*MB*) as a proxy for growth opportunities. Larger firms tend to have lower *IVOL* (Pástor and Pietro 2003). Therefore, we control for size (*SIZE*), which is measured by the natural log of the market value of equity. Brown and Kapadia (2007) suggest that the dividend payout ratio is negatively correlated to the *IVOL*. Therefore, we control our model's dividend payout ratio (*DPO*). Pástor and Pietro (2003) show a negative association between a firm's age and *IVOL*, so we include the natural log of a firm's age (AGE) as a control variable. Chan et al. (2001) show that firms with high R&D expenditure exhibit higher volatility. Therefore, we include R&D expenditure scaled by total assets to control for R&D spending.

In addition, we control for information uncertainty measured by the standard deviation of the analysts' forecasts of firms' EPS (*DISP*) and information asymmetry proxied by bid–ask spread (*BIDASK*). We follow Zhang (2015) and control for cash holdings (*CASH*) and profitability, which are measured by cash divided by total assets and ROA, respectively. These two variables are expected to be negatively correlated with firms' risk. Prior literature suggests that competition is an essential determinant of *IVOL* (Gaspar and Massa 2006; Irvine and Pontiff 2009). Therefore, we control market competition by including the Herfindahl–Hirschman Index (*HHI*). Additionally, we follow Zhang's (2015) control for asset tangibility. Furthermore, we add the lagged values of the *IVOL* to account for volatility persistence (Wei and Zhang 2006). Detailed variable descriptions are provided in Appendix A.

## 4. Empirical Results

### *4.1. Univariate Analysis*

This section conducts a univariate analysis to examine the relationship between *IVOL* and patents. To further explore our sample, we divide our sample into firms that invest in R&D projects and firms with no R&D expenditure (firms that report no R&D activities). Table 3, panel A compares the mean *IVOL* and other control variables for both groups. The analysis shows that firms investing in R&D projects have higher *IVOL*, size, market to book ratio, cash holdings, and cash flow volatility, indicating that such firms that engage in risky long-term projects are large firms with more growth opportunities and higher cash flow volatility. On the other hand, positive R&D firms have lower leverage, dividend payout ratio, bid–ask spread, profitability, and asset tangibility. These results are consistent with the finding of Phillips and Zhdanov (2013).

Similarly, we conduct the same analysis after classifying firms in our sample into patent and no-patent firms. As shown in Table 3, panel B, firms with patents have lower volatility, leverage, cash flow volatility, bid–ask spread, and ROA, indicating that firms producing patents have a healthy financial status, rely less on debt, and have lower volatility and bid–ask spread. These findings are consistent with the results of Balasubramanian and Sivadasan (2011).

Table 4 shows the Pearson correlation matrix for all the variables. The negative association between *IVOL* measures and *PAT* provides preliminary evidence that is consistent with our first hypothesis. However, this univariate analysis is only suggestive because it does not consider other variables. Thus, we rely on the subsequent analyses to make an inference about the proposed hypotheses. In addition, the bivariate correlations between the independent variables are low; hence, multicollinearity is not a problem in our analyses.

**Table 3.** Comparison of means test. Panel A shows the comparison of means *t*-test after classifying the firms in our sample as No-R&D firms or R&D firms. Panel B shows the comparison of means *t*-test after classifying the firms in our sample into firms with no patents and firms with patents. The *t*-statistic is adjusted for unequal variance. The sample period is from 1982 to 2015. ***, **, and * denote significant two-tailed *p*-values ≤ 1%, 5%, or 10%, respectively.

| Panel A | | | | | |
|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **(2–4)** |
| | **No R&D Firm** | | **R&D Firms** | | |
| **Variable** | **N** | **Mean** | **N** | **Mean** | **Difference** |
| $IVOL\_MM_{it}$ | 38,610 | 0.512 | 39,313 | 0.548 | −0.0359 *** |
| $IVOL\_FF3_{it}$ | 38,610 | 0.491 | 39,313 | 0.524 | −0.0330 *** |
| $IVOL\_C4_{it}$ | 38,610 | 0.482 | 39,313 | 0.514 | −0.0325 *** |
| $PAT_{it}$ | 38,610 | 0.035 | 39,313 | 0.407 | −0.372 *** |
| $DISP_{it}$ | 21,120 | 0.105 | 22,707 | 0.108 | −0.003 |
| $CFVOL_{it}$ | 38,610 | 0.124 | 39,313 | 0.139 | −0.0152 *** |
| $SIZE_{it}$ | 38,610 | 5.360 | 39,313 | 5.537 | −0.177 *** |
| $AGE_{it}$ | 38,610 | 2.744 | 39,313 | 2.749 | −0.005 |
| $MB_{it}$ | 38,610 | 2.322 | 39,313 | 3.272 | −0.950 *** |
| $LEV_{it}$ | 38,610 | 0.403 | 39,313 | 0.280 | 0.123 *** |
| $CASH_{it}$ | 38,610 | 0.112 | 39,313 | 0.241 | −0.129 *** |
| $DPO_{it}$ | 38,610 | 0.165 | 39,313 | 0.154 | 0.0103 *** |
| $BIDASK_{it}$ | 38,610 | 0.034 | 39,313 | 0.027 | 0.007 *** |
| $ROA_{it}$ | 38,610 | 0.110 | 39,313 | 0.048 | 0.0623 *** |
| $HHI_{it}$ | 38,610 | 0.067 | 39,313 | 0.069 | −0.002 *** |
| $TANG_{it}$ | 38,608 | 0.370 | 39,313 | 0.200 | 0.1702 *** |

| Panel B | | | | | |
|---|---|---|---|---|---|
| | **No Patents Firm** | | **Firms with Patents** | | **(2–4)** |
| **Variable** | **N** | **Mean** | **N** | **Mean** | **Difference** |
| $IVOL\_MM_{it}$ | 51,602 | 0.553 | 26,321 | 0.484 | 0.070 *** |
| $IVOL\_FF3_{it}$ | 51,602 | 0.531 | 26,321 | 0.462 | 0.069 *** |
| $IVOL\_C4_{it}$ | 51,602 | 0.521 | 26,321 | 0.453 | 0.068 *** |
| $R\&D_{it}$ | 51,602 | 0.103 | 26,321 | 0.320 | −0.217 *** |
| $DISP_{it}$ | 25,994 | 0.111 | 17,833 | 0.100 | 0.0112 *** |
| $CFVOL_{it}$ | 51,602 | 0.135 | 26,321 | 0.125 | 0.010 *** |
| $SIZE_{it}$ | 51,602 | 5.018 | 26,321 | 6.296 | −1.278 *** |
| $AGE_{it}$ | 51,602 | 2.684 | 26,321 | 2.868 | −0.183 *** |
| $MB_{it}$ | 51,602 | 2.584 | 26,321 | 3.228 | −0.644 *** |
| $LEV_{it}$ | 51,602 | 0.367 | 26,321 | 0.291 | 0.076 *** |
| $CASH_{it}$ | 51,602 | 0.155 | 26,321 | 0.221 | −0.066 *** |
| $DPO_{it}$ | 51,602 | 0.147 | 26,321 | 0.183 | −0.036 *** |
| $BIDASK_{it}$ | 51,602 | 0.036 | 26,321 | 0.020 | 0.017 *** |
| $ROA_{it}$ | 51,602 | 0.082 | 26,321 | 0.073 | 0.008 *** |
| $HHI_{it}$ | 51,602 | 0.068 | 26,321 | 0.068 | −0.000 |
| $TANG_{it}$ | 51,602 | 0.553 | 26,321 | 0.484 | −0.217 *** |

**Table 4.** Pearson correlations between the variables included in the analysis. The sample period was from 1982 to 2015. The correlations in bold are at least significant at the 1% level, and [a] and [b] denote correlations significant at the 10% and 5% level, respectively (the other measures of *IVOL* were removed due to space limitations; the full correlation matrix is available upon request).

| | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | $IVOL\_MM_{it}$ | 1 | | | | | | | | | | | | | | |
| 2 | $PAT_{it}$ | **−0.150** | 1 | | | | | | | | | | | | | |
| 3 | $R\&D_{it}$ | **0.147** | **0.012** | 1 | | | | | | | | | | | | |
| 4 | $DISP_{it}$ | **0.284** | **−0.070** | **−0.153** | 1 | | | | | | | | | | | |
| 5 | $CFVOL_{it}$ | **0.351** | **−0.084** | **0.145** | **0.221** | 1 | | | | | | | | | | |
| 6 | $SIZE_{it}$ | **−0.472** | **0.420** | **−0.480** | **−0.228** | **−0.281** | 1 | | | | | | | | | |
| 7 | $AGE_{it}$ | **−0.296** | **0.215** | **−0.298** | **−0.090** | **−0.198** | **0.300** | 1 | | | | | | | | |
| 8 | $MB_{it}$ | **0.070** | **0.070** | **0.069** | **−0.044** | **0.176** | **0.190** | **−0.075** | 1 | | | | | | | |
| 9 | $LEV_{it}$ | **0.112** | **−0.056** | **0.111** | **0.204** | **0.021** | **−0.232** | **0.075** | **−0.344** | 1 | | | | | | |
| 10 | $CASH_{it}$ | **0.129** | **0.029** | **0.126** | **0.101** | **0.161** | **−0.043** | **−0.189** | **0.234** | **−0.468** | 1 | | | | | |
| 11 | $DPO_{it}$ | **−0.203** | **0.094** | **0.350** | **−0.121** | **−0.124** | **0.213** | **0.148** | **0.031** | **−0.083** | −0.007 [b] | 1 | | | | |
| 12 | $BIDASK_{it}$ | **0.430** | **−0.169** | **−0.203** | **0.157** | **0.194** | **−0.645** | **−0.185** | **−0.107** | **0.260** | **−0.101** | **−0.145** | 1 | | | |
| 13 | $ROA_{it}$ | **−0.388** | **0.081** | **0.439** | **−0.379** | **−0.342** | **0.335** | **0.177** | **−0.136** | **−0.035** | **−0.336** | **0.202** | **−0.180** | 1 | | |
| 14 | $HHI_{it}$ | **−0.029** | **0.008** | **−0.384** | **−0.014** | **0.005** | **−0.076** | **0.041** | **−0.033** | **0.036** | **−0.076** | **−0.010** | **0.085** | **0.031** | 1 | |
| 15 | $TANG_{it}$ | **−0.095** | **−0.054** | **−0.026** | **0.100** | **−0.133** | **0.110** | **0.066** | **−0.128** | **0.219** | **−0.408** | **−0.015** | **0.027** | **0.183** | **−0.037** | 1 |

Table 5, panel A reports the differences in the means and medians of subsamples double-sorted based on R&D spending and *PAT*. Panel B reports double sorting based on *PAT* and *DISP*. Table 5, panel A (a) shows the difference in the means and medians of the entire sample. The results indicate that *IVOL* is negatively correlated to *PAT*. The lowest patent quantile has an average (median) $IVOL\_MM$ of 0.545 (0.467) compared to 0.455 (0.391) in the highest quantile. The difference between the two averages is significant at the 1% level. Panel A (b) through panel A (g) show similar results across all R&D quantiles. An important observation is that the mean (median) *IVOL* monotonically declines as the number of patents increases across all R&D quintiles. These results provide preliminary evidence that *IVOL* is negatively correlated to patents after controlling for R&D spending, supporting our first hypothesis. Additionally, this shows that R&D and patents capture different dynamics of the innovation process. These results are consistent with those of previous studies (e.g., Czarnitzki and Toole 2011).

**Table 5.** Double sorting. Panel A reports the average (median) *IVOL* of firms grouped and sorted based on R&D and patent quantiles over the sample period. The reported *t*-statistic (chi-squared) is for the difference between the mean (median) of the average *IVOL* in the lowest and highest quantiles. Panel B reports the comparison means (median) test based on the variance of analyst forecasts and patent quantiles. The sample period is from 1982 to 2015. *** denotes that the difference between the highest and the lowest quantile is significant *p*-value at the 1% level.

| Panel A: firms grouped and sorted on R&D and patents. | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Patents Quantile** | | **No Patents** | **Lowest** | **2** | **3** | **4** | **Highest** | **H-L** | **$t$-stat/$\chi^2$** | **$p$-Value** |
| (a) Full sample | $IVOL\_MM_{it}$ | Means | 0.551 | 0.545 | 0.531 | 0.507 | 0.455 | 0.360 | −0.184 *** | −33.854 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.529 | 0.521 | 0.506 | 0.484 | 0.433 | 0.343 | −0.178 *** | −34.282 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.519 | 0.512 | 0.497 | 0.475 | 0.424 | 0.335 | −0.177 *** | −34.632 | 0.000 |
| | $IVOL\_MM_{it}$ | Medians | 0.460 | 0.467 | 0.456 | 0.442 | 0.391 | 0.299 | −0.168 *** | 1152.331 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.440 | 0.446 | 0.433 | 0.421 | 0.371 | 0.283 | −0.163 *** | 1167.140 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.432 | 0.438 | 0.425 | 0.414 | 0.364 | 0.278 | −0.161 *** | 1184.536 | 0.000 |
| | $N$ | | 53,537 | 7122 | 5173 | 4559 | 5019 | 5323 | | | |

**Table 5.** *Cont.*

| | Patents Quantile | | No Patents | Lowest | 2 | 3 | 4 | Highest | H-L | $t$-stat/$\chi^2$ | $p$-Value |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (b) No R&D firms | $IVOL\_MM_{it}$ | Means | 0.520 | 0.464 | 0.425 | 0.433 | 0.378 | 0.331 | −0.132 *** | −6.989 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.499 | 0.444 | 0.406 | 0.413 | 0.362 | 0.319 | −0.124 *** | −6.870 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.490 | 0.436 | 0.399 | 0.405 | 0.355 | 0.313 | −0.122 *** | −6.866 | 0.000 |
| | $IVOL\_MM_{it}$ | Medians | 0.428 | 0.390 | 0.364 | 0.363 | 0.317 | 0.272 | −0.118 *** | 67.809 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.410 | 0.372 | 0.348 | 0.346 | 0.303 | 0.261 | −0.111 *** | 63.539 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.402 | 0.365 | 0.341 | 0.339 | 0.298 | 0.257 | −0.108 *** | 61.456 | 0.000 |
| | $N$ | | 35,393 | 2156 | 1080 | 674 | 419 | 258 | | | |
| | **Patents Quantile** | | **No Patents** | **Lowest** | **2** | **3** | **4** | **Highest** | **H-L** | $t$-**stat**/$\chi^2$ | $p$-**Value** |
| (c) R&D (Q1) | $IVOL\_MM_{it}$ | Means | 0.499 | 0.440 | 0.404 | 0.381 | 0.349 | 0.292 | −0.148 *** | −12.239 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.480 | 0.421 | 0.386 | 0.364 | 0.333 | 0.277 | −0.144 *** | −12.337 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.471 | 0.413 | 0.378 | 0.357 | 0.327 | 0.271 | −0.142 *** | −12.381 | 0.000 |
| | $IVOL\_MM_{it}$ | Medians | 0.422 | 0.376 | 0.348 | 0.328 | 0.295 | 0.244 | −0.132 *** | 182.295 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.404 | 0.357 | 0.325 | 0.314 | 0.279 | 0.232 | −0.125 *** | 187.777 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.397 | 0.351 | 0.319 | 0.311 | 0.276 | 0.224 | −0.127 *** | 176.894 | 0.000 |
| | $N$ | | 4304 | 1049 | 705 | 684 | 789 | 631 | | | |
| | **Patents Quantile** | | **No Patents** | **Lowest** | **2** | **3** | **4** | **Highest** | **H-L** | $t$-**stat**/$\chi^2$ | $p$-**Value** |
| (d) R&D (Q2) | $IVOL\_MM_{it}$ | Means | 0.550 | 0.483 | 0.466 | 0.433 | 0.359 | 0.304 | −0.179 *** | −16.682 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.529 | 0.464 | 0.447 | 0.415 | 0.342 | 0.290 | −0.174 *** | −16.941 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.520 | 0.457 | 0.439 | 0.407 | 0.335 | 0.283 | −0.174 *** | −17.157 | 0.000 |
| | $IVOL\_MM_{it}$ | Medians | 0.472 | 0.406 | 0.397 | 0.375 | 0.308 | 0.263 | −0.143 *** | 243.941 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.450 | 0.393 | 0.381 | 0.356 | 0.293 | 0.249 | −0.144 *** | 241.249 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.443 | 0.389 | 0.378 | 0.349 | 0.288 | 0.242 | −0.147 *** | 243.941 | 0.000 |
| | $N$ | | 3574 | 918 | 768 | 703 | 904 | 1285 | | | |
| | **Patents Quantile** | | **No Patents** | **Lowest** | **2** | **3** | **4** | **Highest** | **H-L** | $t$-**stat**/$\chi^2$ | $p$-**Value** |
| (e) R&D (Q3) | $IVOL\_MM_{it}$ | Means | 0.616 | 0.575 | 0.530 | 0.511 | 0.438 | 0.348 | −0.227 *** | −19.933 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.591 | 0.552 | 0.507 | 0.489 | 0.419 | 0.333 | −0.219 *** | −20.143 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.580 | 0.542 | 0.497 | 0.480 | 0.412 | 0.326 | −0.216 *** | −20.226 | 0.000 |
| | $IVOL\_MM_{it}$ | Medians | 0.536 | 0.512 | 0.467 | 0.449 | 0.384 | 0.284 | −0.228 *** | 368.925 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.516 | 0.488 | 0.447 | 0.434 | 0.368 | 0.272 | −0.216 *** | 378.864 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.506 | 0.481 | 0.436 | 0.428 | 0.364 | 0.267 | −0.214 *** | 378.864 | 0.000 |
| | $N$ | | 3488 | 963 | 815 | 752 | 878 | 1256 | | | |
| | **Patents Quantile** | | **No Patents** | **Lowest** | **2** | **3** | **4** | **Highest** | **H-L** | $t$-**stat**/$\chi^2$ | $p$-**Value** |
| (f) R&D (Q4) | $IVOL\_MM_{it}$ | Means | 0.654 | 0.624 | 0.582 | 0.567 | 0.505 | 0.396 | −0.228 *** | −18.588 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.626 | 0.597 | 0.554 | 0.541 | 0.479 | 0.377 | −0.220 *** | −18.840 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.616 | 0.587 | 0.544 | 0.531 | 0.469 | 0.368 | −0.219 *** | −19.153 | 0.000 |
| | $IVOL\_MM_{it}$ | Medians | 0.566 | 0.543 | 0.514 | 0.511 | 0.445 | 0.337 | −0.206 *** | 267.952 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.544 | 0.526 | 0.487 | 0.494 | 0.420 | 0.323 | −0.203 *** | 285.189 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.536 | 0.517 | 0.476 | 0.486 | 0.408 | 0.315 | −0.202 *** | 299.963 | 0.000 |
| | $N$ | | 3455 | 942 | 804 | 775 | 932 | 1244 | | | |
| | **Patents Quantile** | | **No Patents** | **Lowest** | **2** | **3** | **4** | **Highest** | **H-L** | $t$-**stat**/$\chi^2$ | $p$-**Value** |
| (g) R&D (Q5) | $IVOL\_MM_{it}$ | Means | 0.774 | 0.762 | 0.743 | 0.650 | 0.609 | 0.505 | −0.257 *** | −13.663 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.741 | 0.726 | 0.707 | 0.618 | 0.576 | 0.477 | −0.249 *** | −13.915 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.728 | 0.715 | 0.695 | 0.608 | 0.564 | 0.465 | −0.250 *** | −14.184 | 0.000 |
| | $IVOL\_MM_{it}$ | Medians | 0.659 | 0.654 | 0.653 | 0.576 | 0.543 | 0.444 | −0.210 *** | 157.917 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.631 | 0.626 | 0.625 | 0.546 | 0.514 | 0.421 | −0.205 *** | 160.417 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.621 | 0.610 | 0.611 | 0.538 | 0.507 | 0.408 | −0.201 *** | 155.436 | 0.000 |
| | $N$ | | 3323 | 1094 | 1001 | 971 | 1097 | 649 | | | |

**Table 5.** *Cont.*

| Panel B: firms grouped and sorted based on standard deviation of analyst's forecasts and patent quantiles. | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Patents Quantile** | | **No Patents** | **Lowest** | **2** | **3** | **4** | **Highest** | **H-L** | **$t$-stat/$\chi^2$** | **$p$-Value** |
| (a) DISP (Q1) | $IVOL\_MM_{it}$ | Means | 0.384 | 0.387 | 0.382 | 0.389 | 0.355 | 0.299 | −0.089 *** | −9.863 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.367 | 0.370 | 0.364 | 0.371 | 0.339 | 0.285 | −0.085 *** | −9.805 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.361 | 0.364 | 0.357 | 0.365 | 0.333 | 0.279 | −0.085 *** | −9.880 | 0.000 |
| | $IVOL\_MM_{it}$ | Medians | 0.345 | 0.340 | 0.326 | 0.352 | 0.298 | 0.242 | −0.097 *** | 111.829 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.329 | 0.327 | 0.309 | 0.334 | 0.286 | 0.229 | −0.098 *** | 101.714 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.324 | 0.322 | 0.306 | 0.322 | 0.280 | 0.223 | −0.099 *** | 113.910 | 0.000 |
| | *N* | | 5211 | 747 | 570 | 577 | 729 | 945 | | | |
| | **Patents Quantile** | | **No Patents** | **Lowest** | **2** | **3** | **4** | **Highest** | **H-L** | **$t$-stat/$\chi^2$** | **$p$-Value** |
| (b) DISP (Q2) | $IVOL\_MM_{it}$ | Means | 0.403 | 0.417 | 0.411 | 0.425 | 0.395 | 0.323 | −0.093 *** | −9.516 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.385 | 0.398 | 0.391 | 0.404 | 0.375 | 0.309 | −0.089 *** | −9.444 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.379 | 0.391 | 0.384 | 0.397 | 0.366 | 0.303 | −0.088 *** | −9.592 | 0.000 |
| | $IVOL\_MM_{it}$ | Medians | 0.363 | 0.372 | 0.368 | 0.370 | 0.346 | 0.263 | −0.110 *** | 114.346 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.344 | 0.357 | 0.347 | 0.349 | 0.326 | 0.254 | −0.102 *** | 110.178 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.338 | 0.353 | 0.344 | 0.340 | 0.317 | 0.247 | −0.106 *** | 118.591 | 0.000 |
| | *N* | | 5099 | 778 | 612 | 623 | 770 | 883 | | | |
| | **Patents Quantile** | | **No Patents** | **Lowest** | **2** | **3** | **4** | **Highest** | **H-L** | **$t$-stat/$\chi^2$** | **$p$-Value** |
| (c) DISP (Q3) | $IVOL\_MM_{it}$ | Means | 0.431 | 0.451 | 0.457 | 0.462 | 0.422 | 0.356 | −0.095 *** | −8.528 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.411 | 0.431 | 0.435 | 0.441 | 0.401 | 0.337 | −0.093 *** | −8.798 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.404 | 0.422 | 0.427 | 0.433 | 0.393 | 0.330 | −0.092 *** | −8.895 | 0.000 |
| | $IVOL\_MM_{it}$ | Medians | 0.383 | 0.400 | 0.404 | 0.418 | 0.367 | 0.300 | −0.100 *** | 97.455 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.368 | 0.380 | 0.386 | 0.395 | 0.350 | 0.285 | −0.096 *** | 101.484 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.360 | 0.373 | 0.380 | 0.392 | 0.344 | 0.280 | −0.093 *** | 109.787 | 0.000 |
| | *N* | | 5106 | 772 | 709 | 634 | 745 | 797 | | | |
| | **Patents Quantile** | | **No Patents** | **Lowest** | **2** | **3** | **4** | **Highest** | **H-L** | **$t$-stat/$\chi^2$** | **$p$-Value** |
| (d) DISP (Q4) | $IVOL\_MM_{it}$ | Means | 0.486 | 0.513 | 0.526 | 0.516 | 0.482 | 0.411 | −0.103 *** | −7.556 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.463 | 0.488 | 0.500 | 0.491 | 0.455 | 0.386 | −0.102 *** | −7.996 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.454 | 0.479 | 0.491 | 0.483 | 0.444 | 0.376 | −0.103 *** | −8.256 | 0.000 |
| | $IVOL\_MM_{it}$ | Medians | 0.427 | 0.463 | 0.467 | 0.466 | 0.428 | 0.360 | −0.102 *** | 36.980 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.408 | 0.436 | 0.446 | 0.448 | 0.404 | 0.338 | −0.098 *** | 47.732 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.400 | 0.427 | 0.438 | 0.439 | 0.395 | 0.334 | −0.093 *** | 46.313 | 0.000 |
| | *N* | | 5098 | 822 | 685 | 678 | 797 | 685 | | | |
| | **Patents Quantile** | | **No Patents** | **Lowest** | **2** | **3** | **4** | **Highest** | **H-L** | **$t$-stat/$\chi^2$** | **$p$-Value** |
| (e) DISP (Q5) | $IVOL\_MM_{it}$ | Means | 0.580 | 0.613 | 0.635 | 0.620 | 0.590 | 0.503 | −0.110 *** | −5.387 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.553 | 0.583 | 0.603 | 0.590 | 0.559 | 0.476 | −0.107 *** | −5.516 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.540 | 0.573 | 0.592 | 0.578 | 0.547 | 0.464 | −0.110 *** | −5.747 | 0.000 |
| | $IVOL\_MM_{it}$ | Medians | 0.499 | 0.531 | 0.551 | 0.555 | 0.530 | 0.447 | −0.084 *** | 24.164 | 0.000 |
| | $IVOL\_FF3_{it}$ | | 0.475 | 0.510 | 0.527 | 0.531 | 0.499 | 0.417 | −0.092 *** | 27.784 | 0.000 |
| | $IVOL\_C4_{it}$ | | 0.465 | 0.502 | 0.518 | 0.521 | 0.487 | 0.415 | −0.086 *** | 33.003 | 0.000 |
| | *N* | | 5480 | 846 | 631 | 683 | 685 | 430 | | | |

Similarly, Table 5, panel B reports the mean and the median of the sample double sorting based on *DISP* and *PAT* quantiles. The first observation is an inverse relationship between *IVOL* and *PAT* across all *DISP* quantiles. For the lowest *DISP* quantile (Q1), as is shown in panel B (a), the average (median) $IVOL\_MM$ declines from 0.387 (0.340) to 0.299 (0.242). The difference between the two averages (medians) is −0.089 (−0.097) and is significant at the 1% level. In the highest *DISP* quantile (Q5), panel B (e), average (median) $IVOL\_MM$ declines from 0.613 (0.531) in the lowest *PAT* quantile to 0.503 (0.447) in the highest *PAT* quantile. The difference is also significant at the 1% level. Interestingly, the difference between the average (median) *IVOL* in the lowest *PAT* quantile and the highest *PAT* quantile increases as we move up the *DISP* quantile. This indicates that the impact of patents is higher for firms with higher information uncertainty as measured by *DISP*, which is consistent with Hypothesis 1b.

### 4.2. Baseline Results

Table 6 shows the results of the regression model, Equation (1), where *IVOL* proxies are regressed on the control variables. We hypothesized that *IVOL* would be negatively correlated to a firm's innovation after we control for fixed effects. Consistent with our hypothesis, the results show that innovation output has a significant negative relationship with idiosyncratic volatility. In model (1), the coefficient for *PAT* ($\beta_1 = -0.09$) in the regression on *IVOL* is significant at the 1% level. The result is robust to alternative measures of *IVOL*.

**Table 6.** Innovation and idiosyncratic volatility. This table shows the relationship between innovation, measured by the natural log of the number of patents weighted by citations ($PAT_{it-1}$), and different proxies of idiosyncratic volatility ($IVOL\_X_{it}$). The definitions of the variables are provided in Appendix A. Fixed effects are included. The standard errors are clustered by firm and year and are reported in parentheses. The sample period is from 1982 to 2015. ***, **, and * denote significance at the 1, 5, and 10% level, respectively.

| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|
| | $IVOL\_MM_{it}$ | $IVOL\_FF3_{it}$ | $IVOL\_C4_{it}$ | $IVOL\_MM_{it}$ | $IVOL\_FF3_{it}$ | $IVOL\_C4_{it}$ |
| $PAT_{it-1}$ | **−0.099 ***** | **−0.096 ***** | **−0.095 ***** | **−0.026 ***** | **−0.025 ***** | **−0.024 ***** |
| | **(0.002)** | **(0.002)** | **(0.002)** | **(0.007)** | **(0.006)** | **(0.006)** |
| $R\&D_{it-1}$ | **0.053 ***** | **0.050 ***** | **0.050 ***** | **−0.001** | **0.000** | **0.000** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $DISP_{it-1}$ | | | | 0.057 *** | 0.055 *** | 0.057 *** |
| | | | | (0.021) | (0.020) | (0.018) |
| $CFVOL_{it-1}$ | | | | 0.066 *** | 0.064 *** | 0.060 *** |
| | | | | (0.024) | (0.021) | (0.021) |
| $SIZE_{it-1}$ | | | | −0.027 *** | −0.026 *** | −0.027 *** |
| | | | | (0.007) | (0.007) | (0.006) |
| $AGE_{it-1}$ | | | | −0.063 *** | −0.059 *** | −0.058 *** |
| | | | | (0.012) | (0.011) | (0.011) |
| $MB_{it-1}$ | | | | 0.009 *** | 0.009 *** | 0.009 *** |
| | | | | (0.002) | (0.002) | (0.002) |
| $LEV_{it-1}$ | | | | 0.183 *** | 0.175 *** | 0.165 *** |
| | | | | (0.028) | (0.026) | (0.024) |
| $CASH_{it-1}$ | | | | −0.02 | −0.02 | −0.022 * |
| | | | | (0.014) | (0.013) | (0.013) |
| $DPO_{it-1}$ | | | | −0.027 *** | −0.025 *** | −0.025 *** |
| | | | | (0.004) | (0.003) | (0.003) |
| $BIDASK_{it-1}$ | | | | 0.560 *** | 0.618 *** | 0.642 *** |
| | | | | (0.187) | (0.178) | (0.174) |
| $ROA_{it-1}$ | | | | −0.146 *** | −0.135 *** | −0.132 *** |

**Table 6.** *Cont.*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $IVOL\_MM_{it}$ | $IVOL\_FF3_{it}$ | $IVOL\_C4_{it}$ | $IVOL\_MM_{it}$ | $IVOL\_FF3_{it}$ | $IVOL\_C4_{it}$ |
| | | | | (0.029) | (0.027) | (0.025) |
| $HHI_{it-1}$ | | | | 0.073 | 0.082 | 0.079 |
| | | | | (0.094) | (0.088) | (0.086) |
| $TANG_{it-1}$ | | | | 0.063 *** | 0.058 *** | 0.054 *** |
| | | | | (0.017) | (0.017) | (0.016) |
| $IVOL\_X_{it-1}$ | | | | 0.072 *** | 0.069 *** | 0.067 *** |
| | | | | (0.007) | (0.007) | (0.007) |
| ***Constant*** | 0.381 *** | 0.369 *** | 0.363 *** | 0.524 *** | 0.500 *** | 0.505 *** |
| | (0.030) | (0.029) | (0.029) | (0.052) | (0.047) | (0.045) |
| *Year FE* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Firm FE* | Yes | Yes | Yes | No | No | No |
| *Industry FE* | No | No | No | Yes | Yes | Yes |
| *N* | 77,923 | 77,923 | 77,923 | 37,587 | 37,587 | 37,587 |
| ***Adj.*** $R^2$ | 0.162 | 0.159 | 0.159 | 0.523 | 0.520 | 0.520 |
| *No. of firms* | 8256 | 8256 | 8256 | 5548 | 5548 | 5548 |

In models (4), (5), and (6), we regress $IVOL$ proxies on $PAT_{it}$. Fixed effects are introduced to the model to mitigate the impact of endogeneity issues that might arise due to the omitted variables bias and the other control variables besides industry and year fixed effects. The results of the fixed effects regression are similar to the results presented in models (1), (2), and (3). This indicates that these results are not driven by time-variant or time-invariant unobserved heterogeneity.

The results in Table 6 show that the coefficients of most of the control variables are significant and have the predicted sign. Consistent with the previous literature, firms that are larger ($SIZE$), are older ($AGE$), have higher payout ratios ($DPO$), have higher cash holdings ($CASH$), and are more profitable ($ROA$) have a lower $IVOL$. On the other hand, firms with higher information uncertainty ($DISP$), growth opportunities ($MB_{it}$), leverage ($LEV_{it}$), and information asymmetry ($BIDASK_{it}$) have higher $IVOL$.

In an unreported previous robustness check, we repeat the analysis using the subsample of firms with positive R&D firms, positive patents, and firms with positive R&D AND positive patents. The results are similar to the reported results, suggesting that the negative association between $IVOL$ and patents is not driven by the jump from no patents to having positive patents or by innovative firms that have lower $IVOL$ in the first place.

### 4.3. Patents and Information Uncertainty

If patents help investors to predict future firm performance and reduce risk, we should expect this effect to be more pronounced for firms with higher information uncertainty. This is because patents disseminate positive information and reduce the information uncertainty in these firms. To test this hypothesis, we follow Diether et al. (2002) and Zhang (2006) and use $DISP$ as a proxy for information uncertainty. We interact the variable with $PAT$ and add the interaction term to the regression analysis. We expect the parameter estimate to be significant and negative. Table 7 shows the results. Consistent with hypothesis H1.b, the parameter estimate on the interaction term is negative and statistically significant at the 1% level in all specifications. The coefficient on $PAT_{it}$ continues to be negative and statistically significant. These results support the hypothesis that the impact of patents is higher for firms with higher information uncertainty.

**Table 7.** The interaction between innovation, information uncertainty, and idiosyncratic volatility. This table shows the interaction between innovation and information uncertainty and their relationship's effect on idiosyncratic volatility. The definitions of the variables are provided in Appendix A. Fixed effects are included. Standard errors clustered by firm and year are reported in parentheses. The sample period is from 1982 to 2015. ***, **, and * denote significance at the 1, 5, and 10% level, respectively.

| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|
| | $IVOL\_MM_{it}$ | $IVOL\_FF3_{it}$ | $IVOL\_C4_{it}$ | $IVOL\_MM_{it}$ | $IVOL\_FF3_{it}$ | $IVOL\_C4_{it}$ |
| $PAT_{it-1}$ | **−0.036 ***** | **−0.034 ***** | **−0.034 ***** | **−0.021 ***** | **−0.021 ***** | **−0.020 ***** |
| | **(0.005)** | **(0.004)** | **(0.004)** | **(0.005)** | **(0.004)** | **(0.004)** |
| $PAT_{it-1} * DISP_{it-1}$ | **−0.089 ***** | **−0.087 ***** | **−0.083 ***** | **−0.067 **** | **−0.066 **** | **−0.062 **** |
| | (0.031) | (0.029) | (0.028) | (0.030) | (0.028) | (0.028) |
| $R\&D_{it-1}$ | 0.011 ** | 0.011 ** | 0.011 ** | (0.001) | 0.000 | 0.000 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| $DISP_{it-1}$ | 0.207 *** | 0.199 *** | 0.197 *** | 0.070 *** | 0.068 *** | 0.069 *** |
| | (0.020) | (0.019) | (0.019) | (0.020) | (0.019) | (0.019) |
| $CFVOL_{it-1}$ | | | | 0.067 *** | 0.064 *** | 0.061 *** |
| | | | | (0.022) | (0.021) | (0.021) |
| $SIZE_{it-1}$ | | | | −0.027 *** | −0.026 *** | −0.027 *** |
| | | | | (0.003) | (0.003) | (0.003) |
| $AGE_{it-1}$ | | | | −0.063 *** | −0.059 *** | −0.058 *** |
| | | | | (0.007) | (0.007) | (0.007) |
| $MB_{it-1}$ | | | | 0.009 *** | 0.009 *** | 0.009 *** |
| | | | | (0.001) | (0.001) | (0.001) |
| $LEV_{it-1}$ | | | | 0.183 *** | 0.175 *** | 0.165 *** |
| | | | | (0.014) | (0.014) | (0.014) |
| $CASH_{it-1}$ | | | | −0.02 | −0.02 | −0.022 * |
| | | | | (0.013) | (0.012) | (0.012) |
| $DPO_{it-1}$ | | | | −0.027 *** | −0.025 *** | −0.025 *** |
| | | | | (0.003) | (0.003) | (0.003) |
| $BIDASK_{it-1}$ | | | | 0.557 *** | 0.615 *** | 0.639 *** |
| | | | | (0.163) | (0.156) | (0.153) |
| $ROA_{it-1}$ | | | | −0.146 *** | −0.136 *** | −0.132 *** |
| | | | | (0.020) | (0.019) | (0.019) |
| $HHI_{it-1}$ | | | | 0.074 | 0.083 * | 0.080 * |
| | | | | (0.049) | (0.047) | (0.046) |
| $TANG_{it-1}$ | | | | 0.062 *** | 0.056 *** | 0.049 *** |
| | | | | (0.017) | (0.017) | (0.016) |
| ***Constant*** | | | | 0.063 *** | 0.058 *** | 0.054 *** |
| | | | | (0.010) | (0.010) | (0.010) |
| *Year FE* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Firm FE* | Yes | Yes | Yes | No | No | No |
| *Industry FE* | No | No | No | Yes | Yes | Yes |

**Table 7.** *Cont.*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $IVOL\_MM_{it}$ | $IVOL\_FF3_{it}$ | $IVOL\_C4_{it}$ | $IVOL\_MM_{it}$ | $IVOL\_FF3_{it}$ | $IVOL\_C4_{it}$ |
| *N* | 37,587 | 37,587 | 37,587 | 37,587 | 37,587 | 37,587 |
| *Adj.* $R^2$ | 0.493 | 0.489 | 0.489 | 0.524 | 0.520 | 0.520 |
| *No of firms* | 5548 | 5548 | 5548 | 5548 | 5548 | 5548 |

## 5. Conclusions

In this paper, we examine the impact of innovation output on *IVOL*. Using alternative measures of *IVOL* for a large sample of US firms, we find that *IVOL* is negatively associated with innovation output after controlling for several firm characteristics under different model specifications. In addition, we show that the impact of innovation output on *IVOL* is more pronounced in firms with higher information uncertainty, as captured by dispersion in analysts' forecasts. This is consistent with our conjecture that patenting improves information dissemination.

The findings of this paper advance our knowledge of how innovation output affects a firm's risk and how innovative activities are evaluated by the capital market. Our results can help managers to better understand the impact of innovative projects on a firm's risk profile and its capital market implications. This will help them allocate capital effectively and efficiently to their available investment opportunity set. Additionally, our results contribute to our understanding of the behavior of *IVOL*, which affects portfolio diversification, options pricing, and market efficiency.

Similar to other studies, this study has the following limitations. There might be firm-specific or market variables that impact firms' *IVOL* but are not included in the model. Additionally, the paper does not address the impact of innovation characteristics (radical and incremental innovation) on firms' risk levels. Future research should investigate this issue as it may have importance to investors and corporate executives.

**Author Contributions:** Conceptualization, N.M.A. and A.A.A.; methodology, N.M.A. and A.A.A.; software, N.M.A. and A.A.A.; validation, N.M.A. and A.A.A.; formal analysis, N.M.A. and A.A.A.; investigation, N.M.A. and A.A.A.; resources, N.M.A. and A.A.A.; data curation, N.M.A. and A.A.A.; writing—original draft preparation, N.M.A. and A.A.A.; writing—review and editing, N.M.A. and A.A.A.; visualization, N.M.A. and A.A.A.; supervision, N.M.A. and A.A.A.; project administration, N.M.A.; funding acquisition, N.M.A. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Acknowledgments:** We are grateful for the feedback of Adriana Grasso, who was the paper's discussant at the 2019 Southwestern Finance Association conference in Houston, and our thanks extend to all the participants.

**Conflicts of Interest:** The authors have no conflicts of interest to disclose.

## Appendix A

Variable definitions.

| Variable | Definition |
|---|---|
| Dependent variable | |
| $IVOL\_MM_{it}$ | The annualized standard deviation of the residuals of the market model using weekly data. |
| $IVOL\_FF3_{it}$ | The standard deviation of the residuals of the Fama and French three-factor model using weekly data. |

| | |
|---|---|
| $\boldsymbol{IVOL\_C4_{it}}$ | The standard deviation of the residuals of the Carhart four-factor model using weekly data. |
| Innovation proxies | |
| $\boldsymbol{PAT_{it}}$ | The natural log of one plus the number of patents weighted by citations in the seven years following the publication date. |
| $\boldsymbol{R\&D_{it}}$ | R&D expenditure scaled by sales. |
| Control variables | |
| $\boldsymbol{DISP_{it}}$ | Standard deviation of analysts' forecasts from I/B/E/S database scaled by stock price. |
| $\boldsymbol{SIZE_{it}}$ | The natural logarithm of the market value of equity. |
| $\boldsymbol{Age_{it}}$ | The natural logarithm of the number of years the firm is covered in the CRSP or CompStat database, whichever is older. |
| $\boldsymbol{MB_{it}}$ | Market value of firm's equity to the book value of firm's equity. |
| $\boldsymbol{LEV_{it}}$ | The market leverage ratio. |
| $\boldsymbol{CASH_{it}}$ | Cash holdings divided by total assets. |
| $\boldsymbol{CFVOL_{it}}$ | The standard deviation of the operating cash flows. |
| $\boldsymbol{DPO_{it}}$ | Dividend payout ratio. |
| $\boldsymbol{BIDASK_{it}}$ | The absolute value of bid–ask divided by stock price. |
| $\boldsymbol{ROA_{it}}$ | Operating income divided by total assets. |
| $\boldsymbol{HHI_{it}}$ | Herfindahl–Hirschman index. |
| $\boldsymbol{TANG_{it}}$ | Property, plant, and equipment divided by total assets. |

## References

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang. 2006. The Cross-Section of Volatility and Expected Returns. *The Journal of Finance* 61: 259–99. [CrossRef]

Atanassov, Julian. 2013. Do Hostile Takeovers Stifle Innovation? Evidence from Antitakeover Legislation and Corporate Patenting. *The Journal of Finance* 68: 1097–131. [CrossRef]

Balasubramanian, Natarajan, and Jagadeesh Sivadasan. 2011. What Happens When Firms Patent? New Evidence from US Economic Census Data. *The Review of Economics and Statistics* 93: 126–46. [CrossRef]

Bloom, Nick. 2007. Uncertainty and the Dynamics of R&D. *American Economic Review* 97: 250–55. [CrossRef]

Brown, Gregory, and Nishad Kapadia. 2007. Firm-Specific Risk and Equity Market Development. *Journal of Financial Economics* 84: 358–88. [CrossRef]

Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu. 2001. Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk. *The Journal of Finance* 56: 1–43. [CrossRef]

Cao, Charles, Timothy Simin, and Jing Zhao. 2008. Can Growth Options Explain the Trend in Idiosyncratic Risk? *The Review of Financial Studies* 21: 2599–633. [CrossRef]

Carhart, Mark M. 1997. On Persistence in Mutual Fund Performance. *The Journal of Finance* 52: 57–82. [CrossRef]

Cefis, Elena, and Orietta Marsili. 2006. Survivor: The Role of Innovation in Firms' Survival. *Research Policy* 35: 626–41. [CrossRef]

Chambers, Dennis, Ross Jennings, and Robert B. Thompson. 2002. Excess Returns to R&D-Intensive Firms. *Review of Accounting Studies* 7: 133–58.

Chan, Louis K. C., Josef Lakonishok, and Theodore Sougiannis. 2001. The stock market valuation of research and development expenditures. *The Journal of Finance* 56: 2431–56. [CrossRef]

Christensen, Clayton M., Fernando F. Suárez, and James M. Utterback. 1998. Strategies for Survival in Fast-Changing Industries. *Management Science* 44: S207–20. [CrossRef]

Cohen, Lauren, Karl Diether, and Christopher Malloy. 2013. Misvaluing Innovation. *The Review of Financial Studies* 26: 635–66. [CrossRef]

Czarnitzki, Dirk, and Andrew A. Toole. 2011. Patent Protection, Market Uncertainty, and R&D Investment. *The Review of Economics and Statistics* 93: 147–59. [CrossRef]

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina. 2002. Differences of Opinion and the Cross Section of Stock Returns. *The Journal of Finance* 57: 2113–41. [CrossRef]

Eberhart, Allan C., William F. Maxwell, and Akhtar R. Siddique. 2004. An Examination of Long-Term Abnormal Stock Returns and Operating Performance Following R&D Increases. *The Journal of Finance* 59: 623–50.

Fama, Eugene F., and Kenneth R. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33: 3–56. [CrossRef]

Fama, Eugene F., and Kenneth R. French. 1997. Industry Costs of Equity. *Journal of Financial Economics* 43: 153–93. [CrossRef]

Fang, Vivian W., Xuan Tian, and Sheri Tice. 2014. Does Stock Liquidity Enhance or Impede Firm Innovation? *The Journal of Finance* 69: 2085–125. [CrossRef]

Gaspar, José-Miguel, and Massimo Massa. 2006. Idiosyncratic Volatility and Product Market Competition. *The Journal of Business* 79: 3125–52. [CrossRef]

Gu, Lifeng. 2016. Product Market Competition, R&D Investment, and Stock Returns. *Journal of Financial Economics* 119: 441–55.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. 2001. *The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools*. Working Paper 8498. Working Paper Series; Cambridge: National Bureau of Economic Research. [CrossRef]

Hall, Bronwyn H. 1993. The Stock Market's Valuation of R&D Investment During the 1980's. *The American Economic Review* 83: 259–64.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg. 2005. Market Value and Patent Citations. *The RAND Journal of Economics* 36: 16–38.

He, Jie (Jack), and Xuan Tian. 2013. The Dark Side of Analyst Coverage: The Case of Innovation. *Journal of Financial Economics* 109: 856–78. [CrossRef]

Holmstrom, Bengt. 1989. Agency Costs and Innovation. *Journal of Economic Behavior & Organization* 12: 305–27.

Irvine, Paul J., and Jeffrey Pontiff. 2009. Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition. *The Review of Financial Studies* 22: 1149–77. [CrossRef]

Jaffe, Adam B. 1986. Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value. *The American Economic Review* 76: 984–1001.

Knight, Frank. 1921. *Risk, Uncertainty and Profit*. Boston: Hougton Mifflin Company.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. 2017. Technological Innovation, Resource Allocation, and Growth. *The Quarterly Journal of Economics* 132: 665–712. [CrossRef]

Kung, Howard, and Lukas Schmid. 2015. Innovation, Growth, and Asset Prices. *The Journal of Finance* 70: 1001–37. [CrossRef]

Li, Guan-Cheng, Ronald Lai, Alexander D'Amour, David M. Doolin, Ye Sun, Vetle I. Torvik, Amy Z. Yu, and Lee Fleming. 2014. Disambiguation and Co-Authorship Networks of the U.S. Patent Inventor Database (1975–2010). *Research Policy* 43: 941–55. [CrossRef]

Mazzucato, Mariana, and Massimiliano Tancioni. 2012. R&D, Patents and Stock Return Volatility. *Journal of Evolutionary Economics* 22: 811–32. [CrossRef]

Pástor, L'uboš, and Veronesi Pietro. 2003. Stock Valuation and Learning about Profitability. *The Journal of Finance* 58: 1749–89. [CrossRef]

Phillips, Gordon M., and Alexei Zhdanov. 2013. R&D and the Incentives from Merger and Acquisition Activity. *The Review of Financial Studies* 26: 34–78. [CrossRef]

Schumpeter, Joseph A. 1934. *The Theory of Economic Development: An Inquiry into Pofits, Capital, Credit, Interest, and the Business Cycle*. Cambridge: Harvard University Press.

Shiller, Robert J. 2000. *Irrational Exuberance*. Princeton: Princeton University Press. [CrossRef]

Shleifer, Andrei, and Robert W. Vishny. 1997. The Limits of Arbitrage. *The Journal of Finance* 52: 35–55. [CrossRef]

Solow, Robert M. 1957. Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics* 39: 312–20. [CrossRef]

Squicciarini, Mariagrazia, Hélène Dernis, and Chiara Criscuolo. 2013. *Measuring Patent Quality: Indicators of Technological and Economic Value*. Paris: OECD Publishing.

Wei, Steven X., and Chu Zhang. 2006. Why Did Individual Stocks Become More Volatile? *The Journal of Business* 79: 259–92. [CrossRef]

Xu, Bixia. 2006. R&D Progress, Stock Price Volatility, and Post-Announcement Drift: An Empirical Investigation into Biotech Firms. *Review of Quantitative Finance and Accounting* 26: 391–408. [CrossRef]

Zhang, Wei. 2015. R&D Investment and Distress Risk. *Journal of Empirical Finance* 32: 94–114. [CrossRef]

Zhang, X. Frank. 2006. Information Uncertainty and Stock Returns. *The Journal of Finance* 61: 105–37. [CrossRef]