Patent Portfolios and Valuation Uncertainty

Thaddeus Neururer*
University of Akron
ORCID: 0000-0001-5267-796X

Li Wang
University of Akron

Yuxiang Zheng
University of Akron

October 2023

*Corresponding Author: tneururer@ukaron.edu

Funding: A University of Akron Faculty Research Fellowship supported this study.

Disclosure statement: We have no conflicts of interest to report.

Data availability statement: The data that support the findings of this study are available from Compustat, CRSP, and OptionMetrics. Restrictions apply to the availability of these data, which were used under license for this study.

Thaddeus Neururer thanks George Papadakis for helpful discussions.

Patent Portfolios and Valuation Uncertainty

Abstract: This study explores how the stock market perceives the risk associated with a company's patent portfolio. Utilizing a U.S. patent sample, we examine the impact of three key patent portfolio characteristics—total value, total number, and value dispersion—on market-perceived valuation uncertainty as proxied by option-implied volatilities. Our results indicate that a greater total market value of a patent portfolio increases market-perceived uncertainty, whereas a larger number of patents and lower value dispersion decrease it. Also, as options trading is related to investors' demand for risk management and investor disagreements, we find that option market activity decreases with the number of patents but increases with the patent portfolio value and dispersion of patent values in a portfolio, and market demand for put options (downside risk protections) increases with patent portfolio value and decreases with the number of patents in a portfolio. In total, our results suggest that the structure of a firm's patent portfolio is associated with market-perceived uncertainty along with the volume and direction of market hedging activities. We extend prior work by showing that not just the quantity, but also the structure of a firm's patent portfolio influences market risk valuation and management. Our findings have implications for academic researchers, investment professionals, and regulators.

JEL Codes: F3, G1, G3

Keywords: Patents, Uncertainty, Options, Open Interest, Cost of Capital

1. Introduction

The debate over whether internal spending on research and development should be capitalized or expensed has been a contentious topic in accounting literature (for a review, see Lev 2018). Opponents of capitalizing research spending are concerned about about the possibility that the research might not yield successful commercialization results. However, the journey from initial research to a finished product is often a step-by-step process where uncertainty tends to decrease over time. Once a patent is granted, it serves as a milestone of the research progress, and the uncertainty should be, at least partially, addressed. A few studies have documented the value-relevance of patents (e.g., Kogan et al. 2017; Marten 2021). Yet, it's still not clear how investors assess the risk associated with these patents. In this study, we examine how the stock market views the risk associated with a company's collection of patents.

Although prior research suggests that firms' patents, on average, decrease systemic risk and idiosyncratic risk (Bena and Garlappi 2020; Hegde and Mishra 2023), the association between patents and valuation uncertainty is not without tension. Investors face at least two uncertainties when evaluating a patent: commercialization uncertainty and litigation uncertainty. First, the successful commercialization of a patented invention is not guaranteed. Compared to the initial research stage, of course, a patent should mitigate the commercialization uncertainty. However, under the Bayesian framework, whether *market-perceived* valuation uncertainty decreases or not would be based on investors' priors. As Neururer et al. (2016) discussed, signals that deviate sufficiently from investors' priors would increase uncertainty. When a patent reveals an invention that deviates from a company's existing product line, investors might face higher valuation uncertainty in pricing the stock.

Second, a patent is more like a "lottery ticket" than a guarantee of monopoly power (Lemley and Shapiro 2005). After a patent is granted, a firm would face the probability that a competitor would invalidate the focal firm's patent at the patent office by showing that the patent is proceeded by "prior art" (i.e., prior patents or public disclosure that address the same invention). In fact, ensuring the innovativeness of patent applications when granting a patent has been a challenge to the patent office. Furthermore, firms must prepare for litigation to stop others from using their intellectual property. The litigation process could be long and costly, and the outcome would depend on the quality of the original patent document. This litigation risk is even higher for patents on inventions with higher commercial values (Allison et al. 2004). Given the two uncertainties, it is important to examine investors' perceived valuation uncertainty of firms' patents.

In this paper, we examine how valuation uncertainty is affected by the *structure* of the patent portfolio. The patent system is a "winner-takes-all" system. To receive a patent and therefore the monopoly power, a firm needs to specialize in a certain technological area and lead all other firms in this field. Such specialization could naturally result in a concentrated patent portfolio, that is firms tend to focus on certain technological areas and a small number of projects given limited resources. A well-diversified patent portfolio, on the other hand, could mitigate the commercialization uncertainty of the inventions. Moreover, patents in a diversified portfolio could complement each other and more effectively deter potential litigation. We thus expect firms with differing patent portfolio structures to exhibit different uncertainty values.

To empirically examine the association between a firm's patent portfolio and market-perceived uncertainty, we use the Kogan et al. (2017) patent sample. We measure valuation uncertainty using implied volatilities (IVs) from the option market.[1] We examine the valuation uncertainty of all patents a firm received in the past twenty years. We focus on three characteristics of a patent portfolio: (i) the total value of patents, (ii) the total number of patents, and (iii) the standard deviation of patent values.

One innovation of our study is that we examine the number of patents, the valuation of patents, and the diversification of patents simultaneously.[2] As discussed in Section 4, the three characteristics are correlated but have different implications for valuation uncertainty and it is important to adjust for the others when examining one characteristic. Conditional on the number of patents and the value dispersion of the portfolio, we expect the total value of the patent portfolio to have a positive association with

[1] Martin and Wagner (2019) show that IVs are directly connected to expected returns on stocks and, consequently, IVs are also related to firms' cost of equity capital.

[2] To be clear, our use of patent-related statistics means our results and inferences are confined to firms that have filed and been granted patents in the past.

uncertainty measures due to the highlighted risks of implementation. However, due to diversification effects, we expect that, conditional on the total value of the patent portfolio, the number of individual patents to have a negative association with market-based risk measures. Finally, conditional on the other two factors, we expect firm uncertainty to be lower when individual patents in the patent portfolio have similar values (i.e., a lower valuation standard deviation). Again, this would suggest that better-diversified patent portfolios lead to lower market-based uncertainty metrics.

Our empirical results confirm these hypotheses. We find that, on average, market-perceived valuation uncertainty increases with the market value of a patent portfolio, conditional on the total number of patents in the patent portfolio and value dispersion. This finding is consistent with our assumption that investors face significant uncertainty when pricing firms' patents in stock. Furthermore, we find that conditional on the total market value of a patent portfolio, a larger number of patents and a lower scaled standard deviation of patent values decrease market perceived uncertainty. These results hold conditional on several other factors that explain firm uncertainty levels (e.g., firm size, age, and profitability), industry membership, and static firm-level heterogeneity (i.e., firm fixed effects). We also note that our results hold when we use amortized patent values to construct firms' total patent portfolio valuations and valuation dispersions. Moreover, our results hold when our analyses focus on recently granted patents. In total, these results suggest that the structure of a firm's patent portfolio is critical for understanding firm uncertainty, both across firms and within firms. Firm uncertainty is lower for firms with many patents and patents with similar values. Conversely, firm uncertainty is conditionally higher for firms whose patent portfolios are composed of few high-value patents.

We next conduct a series of additional tests and robustness checks. First, we find that the three characteristics of firms' patent portfolios help to explain the cross-section and within-firm variation in option-implied CAPM betas, systematic variances, and idiosyncratic variances. In addition, we find our results are generally robust after controlling for lagged measures of uncertainty such as historical return volatility and prior IV levels. Finally, we investigate option trading as a function of firms' patent portfolio characteristics. Given that options trading is related to investors' demand for risk management products and investor disagreements (e.g., Choy and Wei 2012), we suspect that option market activity is likely connected to firms' patent portfolios. We find that the number of open option contracts, which we use as a proxy for option market activity, decreases with the number of patents but increases with the patent portfolio value and dispersion of patent values in a portfolio. Importantly, these results hold when we control for uncertainty levels and stock market activity and, consequently, this suggests that option market activity is uniquely influenced by firms' patent portfolios. We also examine market demand for put options, which offer downside risk protections, with the patent portfolio characteristics. We find that the put-to-call open interest ratio (our proxy for excess downside risk protection demand) increases with patent portfolio value and decreases with the number of patents in a patent portfolio. In total, these results suggest that the structure of a firm's patent portfolio is associated with market-perceived uncertainty along with the volume and direction of market hedging activities.

Our study contributes to the growing literature about the market valuation of firms' patents. Several recent studies document that stock market investors react positively to patent grants (e.g., Kogan et al. 2017; Marten 2021), suggesting that the commercial value of the patented invention is, at least partially, incorporated into the stock price. Our paper complements these prior studies by showing that investors' valuation of a firm's patented invention goes together with their perceived uncertainty of the patent valuation. The Kogan et al. (2017) market-based measure of patent value has been widely used in the innovation literature. Considering the positive association between this measure and market-perceived valuation uncertainty, researchers should be cautious when interpreting this measure in their study.

Several recent studies also discuss the association between patents and firm risk. Bena and Garlappi (2020) find that patented innovations decrease a firm's fundamental risk, which they attribute to the "winner-takes-all" nature of innovation. Similarly, Hegde and Mishra (2023) examine the idiosyncratic risk of patents and find that idiosyncratic risk decreases when patents increase. Importantly, both studies discussed the average effect of a patent on fundamental risk, that is, on average, the more patents a firm receives, the lower the firm's risk is. Consistent with these two studies, we find that a higher number of patents is associated with a lower valuation risk, holding the total value of patents constant. But different from the prior research, our study documents that, holding the number of patents constant, the higher the market value of a firm's patented innovation is, the higher the valuation risk. This finding complements the prior studies by disentangling the risk implication of the value of patents from that of the number of patents. We also emphasize that beyond the average effect of patents on a firm's risk, the structure of a firm's patent portfolio matters: a more diversified patent portfolio has a lower valuation risk.

Our study should also be of interest to regulators by contributing to the ongoing debate about whether internal spending on research and development (R&D) should be capitalized. The cash flow effect of firms' internal R&D spending has been documented by Lev and Sougiannis (1996). They also find a significant intertemporal association between firms' R&D capital and subsequent stock returns, which they interpret as evidence for either systematic mispricing or compensation for risk. Subsequent studies find empirical evidence that is consistent with both mispricing (e.g., Hirshleifer et al. 2018) and risk premium (Chambers et al. 2002; Lin and Wang 2016). Curtis et al. (2020) document a declining trend of R&D profitability over the past several decades, which they partially attribute to the declining riskiness of R&D activities. Considering the changing nature of firms' innovation activities over time, the International Accounting Standards Board and the U.S. Financial Accounting Standard Board view intangible assets as one of the most important topics on their agendas.[3] Our findings that significant valuation uncertainty exists at the patenting stage of internal R&D activities would suggest regulators be cautious when considering changing the accounting treatment for R&D spending.

The remainder of the paper is organized as follows. In section 2, we develop our hypotheses. In section 3, we describe the data and summary statistics. We present our main results and a battery of robustness tests in section 4. We conclude in section 5.

[3] https://www.wsj.com/articles/the-new-head-of-the-international-accounting-standards-board-outlines-his-priorities-11630936800

2. Hypothesis development

It is well-known (e.g., Fama and French 1993), that the level of firms' assets is negatively correlated with risk. However, when it comes to R&D investment, the input of one of the most valuable intangible assets, empirical evidence suggests a stock premium on it (e.g., Lev and Sougianious 1996; Eberhart et al. 2004). Some studies attribute the stock premium to market underreaction: Hirshleifer et al. (2018) find empirical evidence that the complexity of innovation activities explains the premium. Others view the stock premium as compensation for risk. For example, Chambers et al. (2002) find empirical evidence that the excess returns to R&D-intensive firms are at least partially attributable to risk. Lin and Wang (2016) document that firms with high R&D intensity are more likely to become takeover targets and that a higher takeover probability leads to higher risk.

Taking the risky nature of R&D activities as a given, a patent signals the successful progress of a firm's R&D activities and should decrease market uncertainty. Kogan et al. (2017) document an average positive market reaction to patent grants. From a disclosure perspective, Glaeser et al. (2020) show that patenting is a disclosure decision that decreases investors' uncertainty and firms use patents to disclose successful R&D outcomes in response to investors' expectations. A few studies also test patents in addressing the fundamental uncertainty of innovation activities and document a negative association between the size of the patent portfolio and firms' fundamental risk. Bena and Garlappi (2020) find that an increase in a firm's number of patents decreases its own beta and increases rivals' beta. Hegde and Mishra (2023) show a negative association between the number of patents and firms' cost of capital.

However, when investors price a firm's patents in the capital market, two uncertainties arise with the valuation: commercialization uncertainty and litigation uncertainty. First, from a patent to a final product, it requires the firms' follow-up investment in both tangibles and intangibles. There is no guarantee that a firm will always pursue the research agenda and push the innovation to the final commercialization stage. In fact, a large proportion of patents are filed and then abandoned (Allison et al. 2004). Li (2011) also finds that R&D-intensive firms are more likely to suspend/discontinue R&D

projects due to financial constraints. Therefore, large commercialization uncertainty exists even after an innovation is patented.

One might argue that compared to the initial research stage, receiving a patent should, at least partially, mitigate the commercialization uncertainty. While it might be intuitively true that the economic uncertainty should decrease as the innovation progresses, under a Bayesian framework, whether the *market-perceived* valuation uncertainty increases or not would depend on the investors' priors. Neururer et al. (2016) show that when earnings news deviates enough from investors' priors, market-perceived uncertainty increases, which they call the "regime shifting" scenario. The regime shifting case is even more relevant when it comes to the innovation activities: firms' disclosure on initial research activities is very limited and investors have limited knowledge about the invention before the patent is published. For example, when Apple Inc. received the patent on its auto-driving technology, investors would consider the potential release of Apple cars in their valuation model. This shift, compared to investors' priors which focus on Apple's traditional products, would increase the market-perceived uncertainty.

Second, as Lemley and Shapiro (2005) argued, a patent is never a guarantee of monopoly power, but rather a probabilistic right of the patent owner to try to exclude competitors in the product market. On average, a patent examiner spends only 18 hours per application reading the application, searching for and reading prior art, comparing the prior art to the application, and making a decision (Lemley 2001). Therefore, the validity of granted patents would likely be at risk. When the validity of a firm's patent in commercial use is challenged, the firm value could decrease significantly. For example, when a U.S. judge invalidated Acorda's multiple sclerosis drug patents, the stock price dropped by 24% before trading was halted. In addition, a patent would not automatically exclude others from using the invention. After receiving a patent, a firm needs to be prepared to enforce the patent protection; that is, identifying other parties who are using the firm's patented invention illegally and bringing legal action against those businesses. This will be a continuous, lengthy, and costly process. This risk would be even higher for inventions with a higher commercial value (Allison et al. 2004).

Taking the above discussion, our first hypothesis follows[4]:

H1: Ceteris paribus, the market value of a firm's patent portfolio is positively associated with market-perceived uncertainty.

We next study the association between the structure of the patent portfolio and firm risk. Specifically, we are interested in whether a diversified patent portfolio lowers valuation uncertainty compared to a concentrated patent portfolio. On the one hand, the patent system is a "winner-takes-all" system. To gain monopoly power through patents, a firm must lead all other peers in the innovation process. This would make the firm naturally specialize in certain projects, given the limited resources. This would mean that a diversified portfolio would not be associated with lower firm risk because commercialization efforts would be spread too thin.

On the other hand, traditional asset pricing theory predicts that diversification should decrease risk. A well-diversified patent portfolio could be less risky compared to a portfolio that concentrates on a few, important patents. First, as discussed before, the legal protection from a single patent is probabilistic. Having multiple related patents from the same technological field could generate synergy and provide more well-rounded protection, therefore mitigating litigation uncertainty. Furthermore, having multiple parallel projects could diversify away the risk that a firm's innovation activities become a total failure. Having multiple ongoing research lines with similar importance should be less risky compared to having one overweighted leading project. The above discussion leads to our second hypothesis:

H2: Ceteris paribus, the value diversification of a firm's patent portfolio is negatively associated with market-perceived uncertainty.

3. Empirical models, variable definitions, and sample construction

3.1 Empirical models and variable definitions

[4] Our hypotheses are one-sided but for the reported statistics we use two-sided tests. Consequently, our reported tests are conservative.

To investigate the association between patent portfolio characteristics and investor uncertainty, we use the following (full) models:

$$LOG\_IMPVOL_{it} = \alpha_1 LOG\_PATVAL_{it} + \alpha_2 LOG\_PATNUM_{it} + \alpha_3 LOG\_DISP_{it} + \alpha_4 LOG\_RNDEXP_{it} + \alpha_5 LOG\_AT_{it} + \alpha_6 LOG\_BTM_{it} + \alpha_7 LEV_{it} + \alpha_8 ROA_{it} + \alpha_9 LOSS_{it} + \alpha_{10} LOG\_AGE_{it} + \text{Industry x Month Fixed Effects} + \varepsilon_{it} \quad (1)$$

$$LOG\_IMPVOL_{it} = \beta_1 LOG\_PATVAL_{it} + \beta_2 LOG\_PATNUM_{it} + \beta_3 LOG\_DISP_{it} + \beta_4 LOG\_RNDEXP_{it} + \beta_5 LOG\_AT_{it} + \beta_6 LOG\_BTM_{it} + \beta_7 LEV_{it} + \beta_8 ROA_{it} + \beta_9 LOSS_{it} + \beta_{10} LOG\_AGE_{it} + \text{Industry x Month Fixed Effects} + \text{Firm Fixed Effects} + \varsigma_{it} \quad (2)$$

In (1) and (2), the dependent variable is the natural log of the at-the-money (ATM) 30-day IV for firm *i* and the end of month *t* (*LOG_IMPVOL*). We set the ATM IV to the mean of the 50 delta put and call IVs on the last trading day of the month using the OptionMetrics surface files.[5] It is unclear if investor uncertainty should be measured in variance or volatility terms, but the use of the log of the IV makes that choice irrelevant.

The main three independent variables provide information about a firm's patent portfolio. First, to examine H1, we calculate the total market value of a firm's patent portfolio. For each patent, we use the market-based measure of patent value from Kogan et al. (2017).[6] Kogan et al. (2017) measure the commercial value of a patent as the product of the estimated stock return due to the value of the patent times the market capitalization. The estimate of the patent-related stock return is based on the three-day idiosyncratic return of a firm following the patent grant. We then measure *LOG_PATVAL* as the natural log of the sum of patent values among valid patents in the firm's portfolio at the beginning of month *t*. For a patent to be included in the portfolio, it must meet two conditions: i) the patent's issue date must be before the first day of month *t*, and ii) the patent's filing date must be less than 20 years before the start of the month *t*.

5 Some studies use "model-free" IVs (e.g., Neururer et al. 2020) but Smith and So (2022) suggest that the difference between ATM IVs and the model-free values are small for shorter durations.

6 We thank Kogan et al. (2017) for sharing their data on patent commercial value. Data are available at https://github.com/KPSS2017. The research team of Kogan et al. (2017) periodically updates the database to include more recent patents. We use the version released in June 2021.

Next, we construct two measures that capture different aspects of patent portfolio diversification. First, a patent portfolio is more diversified if, holding the total value of a patent portfolio constant, there are more patents in the portfolio. We calculate *LOG_PATNUM* as the natural log of the number of valid patents in the firm's portfolio at the beginning of month *t*. Second, conditional on the other two factors, we expect firm uncertainty to be lower when individual patents in the patent portfolio have similar values (i.e., a lower valuation dispersion). We construct the measure *LOG_DISP* as the standard deviation of the patents' value (*PAT_STDEV*) scaled by the mean of the patents' value (*PAT_MEAN*). As *LOG_DISP* increases, this would indicate that a firm's patents have a greater valuation dispersion: some patents are highly valuable, while others are much less so. Consequently, we expect to estimate a positive regression coefficient for *LOG_DISP*.

In later tests, we redefine our variables *LOG_PATVAL, PAT_MEAN*, *PAT_STDEV,* and *LOG_DISP* to account for patent economic amortization. We thus create the variables *PAT_WTDMEAN* and *PAT_WTDSTDEV* to create a weighted mean and standard deviation for a firm's patent portfolio value. Following prior literature (Bloom et al. 2013; Cao et al. 2023), we use a 15% annual depreciation rate to weigh each patent's commercial value based on its age (i.e., the filing date marks the start date for the patent). The use of the discounting function weights the patent portfolio value, its mean value, and the standard deviation toward more recent patents in the firm's portfolio. Conversely, the use of the weighted standard deviation requires more patent values and, thus, we must delete additional observations when we use the *PAT_WTDSTDEV* measure.[7] We then create the variables *LOG_PATWTDVAL* defined as the natural log of *PAT_WTDMEAN* times the number of valid patents and *LOG_WTDDISP* defined as the natural log of the ratio of *PAT_WTDSTDEV* to *PAT_WTDMEAN*.

[7] To estimate the weighted standard deviation, we use the function 'wtd.var' from the R package Hmisc (version 4.5-0).

We also include several control variables in our model that are likely associated with firm uncertainty and a firm's patent portfolio.[8] We first define *LOG_RNDEXP* as the natural log of the firm's total discounted R&D expenses from the prior twenty years plus $1 million.[9] We set the R&D expense to $1 million if the total value is missing or zero (i.e., *LOG_RNDEXP* is equal to zero). We also define *LOG_AT* as the natural log of the firm's book assets, *LOG_BTM* as the natural log of the firm book-to-market ratio at the end of the prior quarter, and *LEV* as book liabilities divided by book assets. We expect a negative coefficient for *LOG_AT* and positive coefficients for *LOG_BTM* and *LEV*. We also define two financial performance measures: *ROA* is defined as income before extraordinary items divided by book assets from the prior quarter and *LOSS* is a binary variable set to one if *ROA* is less than zero. We expect a negative (positive) coefficient for *ROA* (*LOSS*) indicating that better financial performance is associated with lower investor uncertainty. Finally, we include the variable *LOG_AGE* which is defined as the natural log number of days between the option measurement date and the firm's first appearance in Compustat. Investors tend to have lower uncertainty about old firms (e.g., Pastor and Veronesi 2003) and, consequently, we expect a negative coefficient for *LOG_AGE*.

All regressions are estimated using OLS and include industry crossed with month-fixed effects. The use of the industry-month fixed effects controls for time-varying industry shocks and adjusts the variables by industry-month averages.[10] We define industries by two-digit SIC codes. We also winsorize all continuous variables at the 1st and 99th percentiles, standardize all continuous independent variables to have unit variance and a mean of zero, and cluster all standard errors by months and by firms.

3.2 Sample construction

8 The additional control variables are calculated using quarterly Compustat data. To link the Compustat data to the option data, we use the field *rdq* (the firms' earnings report date). We then chose the Compustat data that had an earnings report date that was closest to but before the option data date.

9 R&D expenses are in millions of dollars in Compustat. Because total R&D expense may be zero, we need to add a constant to the raw value of the expense to then take the log. As below, we use a 15% discount rate for prior R&D expenses.

10 All our empirical models use industry-month fixed effects and, thus, we do not need to include other market-level variables.

To construct our sample, we first note that our patent data begins in 1980. Because the legal life of the patent is roughly 20 years, we start our option data in 2000. Our options data ends in 2017.

Table 1 displays the sample selection process. We start with 654,399 monthly option observations representing 8,069 firms. Next, we delete 86,851 observations because of missing CRSP data and an additional 87,851 observations due to missing Compustat data. We next remove 2,680 observations because CRSP and OptionMetrics disagree too much on the underlying price. More specifically, we remove observations where the log ratio of the option-implied ATM strike price and CRSP stock price were more than 10% in absolute value. Next, because our tests require patent data, we remove 239,922 observations because the number of patents for the firm was zero. We also remove 453 observations because we could not calculate the total value of the patent portfolio. Finally, we remove 25,876 observations because we could not generate a *PAT_DISP* value. Our final sample has 211,594 observations for 2,380 unique firms.

4. Summary information

4.1 Sample statistics

Panel A of Table 2 displays the number of observations by year. First, it is clear the number of observations and the number of firms represented in the sample increase throughout the sample period. This is consistent with prior literature (e.g., Smith and So 2022) that documents that option coverage for firms has increased over the last two decades. In addition, we see the median number of patents per firm across the represented firms increased. This indicates that firms' patent portfolios expanded during the examined period.

Panel B of Table 2 shows the number of firms and the median number of patents based on the Fama-French 12 industry classification. The largest industry based on the number of observations is

Business Equipment (*N* = 68,109) with 822 firms represented. However, as evident from the data, there is a large variation in the number of patents held across the industries. The largest two industries in terms of the median number of patents are Chemical and Allied Products (median *NUMPAT* = 202) and Consumer Durables (median *NUMPAT* = 97). On the other hand, firms in the Wholesale, Retail, and Some Services (median *NUMPAT* = 6) and Utilities (median *NUMPAT* = 7) hold relatively few patents. Thus, the use of our industry-month fixed effects appears warranted.

4.2 Variable summary statistics

Panel A of Table 3 shows the summary statistics for the main variables of the study. We find the median *LOG_IMPVOL* (IV) value is -0.930. This value corresponds to an expected annualized stock volatility of 39.5%. Moreover, the median value of *LOG_PATVAL* is 5.249, suggesting the average patent portfolio value is about $190 million, which is economically significant relative to the $1,450 million median value of the total assets (about 13%) suggested by the median *LOG_AT* of 7.279. Because of our use of options data, it is not surprising our sample skews towards larger firms. In addition, using the median value for *LOG_NUMPAT*, we find the average number of patents in a firm's patent portfolio is roughly 34. This generally agrees with the values in Table 2.

As expected, the average *LOG_BTM* value is negative indicating that firms' stocks trade above their book values. We find that the average *LEV* value is around 0.472 although leverage varies considerably across industries (untabulated). We also find the average firm reports a profit (mean *LOSS* = 0.264) and the median *ROA* is 1.1%.[11] Finally, the median value for *LOG_AGE* suggests the average firm has existed for about 6,974 days or approximately 19 years.

Panel B of Table 3 presents the correlation table of key variables in the empirical analysis. We present the Pearson correlations in the upper-right portion of the matrix and the Spearman correlations in the bottom-left part of the table. Correlations that are significant at the one percent level using a two-sided test are displayed in bold. As expected, we find the number of patents and the total value of the patent

[11] To be clear, *ROA* is based off quarterly values. This accounts for its seemingly low average value.

portfolio are highly correlated, but the dispersion of the patent values is negatively related to the number of patents and the total value of the patent portfolio. Moreover, we find that firms with high levels of R&D spending (*LOG_RNDEXP*) typically have more patents and larger patent portfolio values. Finally, we note that IVs are negatively correlated with firm size and age and are higher for firms that are not profitable.

5. Empirical results

5.1 Main results

We present the main regression results in Table 4. We first use the unweighted variables in columns (1) and (2). Column (1) shows the regression results with industry-by-month fixed effects while column (2) includes both firm and industry-by-month fixed effects. Again, our first hypothesis predicts that the total value of the patent portfolio is positively associated with valuation uncertainty levels conditional on the other factors while our second hypothesis predicts that, after holding the total value of patents constant, a more diversified patent portfolio is associated with a lower level of valuation uncertainty. We find that the coefficients on *LOG_PATVAL* are significantly positive. In column (1), the coefficient for *LOG_PATVAL* is 0.032 (*t*-stat = 2.32), and in column (2) the estimated coefficient is 0.180 (*t*-stat = 6.99). This suggests that conditional on the other variables, higher total patent values are associated with higher investor uncertainty as proxied by IVs. We also estimate strong negative coefficients for *LOG_PATNUM* (*t*-stats of 3.58 and 8.96 in columns 1 and 2, respectively). Thus, conditional on the other factors, more patents in a firm's portfolio are associated with lower investor uncertainty. Combined, these results suggest that the structure of a firm's patent portfolio is critical for explaining investor uncertainty.

Furthermore, we find positive coefficients for *LOG_DISP* (*t*-stats of 12.87 and 4.90 in columns 1 and 2, respectively). This indicates that firms with patent values that are more similar have lower uncertainty. Conversely, uncertainty levels increase as patent values are spread out more widely in a portfolio. This is conditional on holding the number of patents and the total value of the patent portfolio constant. This again is consistent with our expectations; firm uncertainty is lower for firms that have greater diversification of patent values, both in terms of the number and the spread of the patent values.

In columns (3) and (4), we repeat the analysis with the weighted version of our main independent variables (N = 190,598). The results are qualitatively similar to those in columns (1) and (2). We again find negative and significant coefficients for *LOG_PATNUM* and positive and significant coefficients for *LOG_PATWTDVAL* and *LOG_WTDDISP*. The results suggest that investor uncertainty is lower for firms that have many patents and whose patent values are similar but uncertainty increases as the total value of the patent portfolio increases.

We note that the control variables generally obtain their predicted signs. Focusing on the results without firm fixed effects (columns (1) and (3)), we find that IVs are lower for firms with higher levels of book assets (*LOG_AT*), have higher profitability (*ROA*), and are older (*LOG_AGE*). We also find that uncertainty is higher for firms with higher book-to-market ratios (*LOG_BTM*), leverage (*LEV*), and that report a loss (*LOSS*). Interestingly, *LOG_RNDEXP* is not significant in the regressions without the firm fixed effects. However, when using the firm fixed effects in columns (2) and (4), the coefficients for *LOG_RNDEXP* are significant and negative.

5.2 Recent patents

Our prior results may be overly influenced by older patents. While we test our results with discounted values and weighted statistics, it is still possible that the discounting factor overvalues older patents. Consequently, as a further test, we focus our results on patents that have been filed and issued recently. We thus redefine our main independent variables to only use the patent value for patents that were filed in the last five years (60 months). We call our new variables *LOG_PATVAL60M* (the log total value of the patents), *LOG_PATNUM60M* (the log number of patents), and *LOG_DISP60M* (the log of the patent value dispersion). Because the number of patents drops considerably and the time from the filings is short, we only use unweighted statistics for this analysis. The number of available observations for this analysis is N = 157,064. We display the results in Table 5.

In column (1) we show the results when not using the firm fixed effects. Consistent with the prior results, we estimate a positive and significant coefficient for *LOG_PATVAL60M* (t-stat = 3.97), we find a negative and significant coefficient for *LOG_PATNUM60M* (t-stat = 3.91), and estimate a positive and significant coefficient for *LOG_DISP60M* (t-stat = 12.60). These results again enforce the finding that firm uncertainty is increasing as the total value of the patent portfolio increases, but this is offset by the effect of having more patents and patents that have similar valuations. We display the regression results when including the firm fixed effects in column (2); the results are like those displayed in column (1). In short, the results of this section show that our results hold when we focus on patents that are recently issued to firms.

5.3 Implied betas

We next analyze the relationship between our main test variables and implied equity beta. While this analysis is similar to the analyses in the prior sections, it is also possible that firms that our examined variables have offsetting effects on correlations with the market portfolio. This could lead to a situation where, even though IVs are associated with the structure of a firm's patent portfolio, a firm's CAPM beta would be unassociated with the same factors.

To construct a forward-looking equity beta, we start with the standard formula of beta:

$$\beta_{i,M}=\rho_{i,M}\frac{\sigma_i}{\sigma_M}$$

Here, $\beta_{i,M}$ is the equity beta for firm i to the market portfolio, σ_i is the volatility of returns for firm i, σ_M is the volatility of returns for the market, and $\rho_{i,M}$ is the correlation of the returns for firm i and the market. To construct the implied beta (*IMPBETA*), we substitute the 30-day IV for firm i for σ_i and substitute the concurrent value of the VIX[12] (divided by 100) for σ_M. However, because there is no easy way to generate an implied correlation from the equity options market, we instead substitute the historical correlation of the stock returns to the market. This method has been used by prior literature to construct a

[12] The VIX is the CBOE's volatility index which is derived from short-term options on the S&P 500.

hybrid equity beta that incorporates forward-looking information (Callen and Lyle 2020).[13] Our estimate of $\rho_{i,M}$ is based on three months of daily returns using the CRSP weight-value index as the market return proxy.

We then replace *LOG_IMPVOL* with our estimates of *IMPBETA* in our regression models as the dependent variable. The results are presented in columns (1) and (2) of Table 6. In column (1) we display the results when not incorporating the firm fixed effects. Like the results of the prior section, we find that implied betas are positively associated with the total value of the portfolio (*LOG_PATWTDVAL*; *t*-stat = 5.34) but are negatively associated with the number of patents in the portfolio (*LOG_PATNUM*; *t*-stat = 5.49). Moreover, we also find that implied betas are positively related to firms' patent value dispersion (*LOG_WTDDISP*; *t*-stat = 8.56). These results show that the cross-section of implied betas is partially explained by the structure of firms' patent portfolios.

In column (2) of Table 6 we add the firm fixed effects. The results are similar to those of column (1) even after controlling for unobserved firm-level heterogeneity. We again find that implied betas are negatively associated with the number of patents in firms' portfolios, but implied betas are positively associated with the total value of the patent portfolio and the dispersion of those values. Again, these results highlight the basic insight that the composition of the patent portfolio is critical to understanding the relationship between patent values and the cost of capital proxies.

We also calculate the log of the implied systematic and idiosyncratic variance. To do so, we employ the following formulas:

$$LOG\_IMPSYSVAR = \ln\left(IMPBETA_{i,M}^{2} \times \sigma_{M}^{2}\right)$$

$$LOG\_IMPIDIOVAR = \ln\left(\sigma_{i}^{2} - \left[IMPBETA_{i,M}^{2} \times \sigma_{M}^{2}\right]\right)$$

Here, *LOG_IMPSYSVAR* (*LOG_IMPIDIOVAR*) is the log level of implied systematic (idiosyncratic) variance. We display the regression results when using these two variables in columns (3)

[13] Callen and Lyle (2020) find that equity return correlations with market returns do not vary much (i.e., they are 'sticky').

– (6) of Table 6 after removing observations where the two values could not be calculated ($N = 190{,}571$). The results of these regressions generally agree with the results when using *IMPBETA* as the dependent variable. We again estimate positive and significant coefficients for *LOG_PATWTDVAL* and *LOG_WTDDISP* but we estimate negative and significant coefficients for *LOG_PATNUM*. This suggests that the patent portfolio statistics help to explain both expectations of future systematic and idiosyncratic risk. The exception to this is that the estimated coefficient for *LOG_WTDDISP* in column (4) is not significant at traditional levels (t-stat = 1.42). This suggests that the within-firm effect of patent value dispersion on expected systematic risk is near zero.

5.4 Robustness tests

We next run a set of robustness tests. Our goal with these tests is to see if firms' patent portfolios can help explain firms' IV levels even after accounting for lagged measures of uncertainty. However, it should be noted that these tests may be overly restrictive because firms' patent portfolios may influence these lagged measures of uncertainty. Thus, we view the results of these tests to be conservative.

We first define *LOG_HISTVOL* as the natural log of a firm's three-month historical return volatility. We expect that, due to volatility persistence, prior return volatility will be highly related to IV levels. In Table 7, columns (1) and (2), we display the regression results when including *LOG_HISTVOL* as a control variable. As expected, in both regressions, we find the estimated coefficients for *LOG_HISTVOL* are positive and highly significant. Importantly, when we do not include the firm fixed effects in column (1), we find that both *LOG_PATWTDVAL* and *LOG_PATNUM* are no longer significant. This suggests that conditional on the recent historical return volatility for a firm, the number of patents and the total value of the patent portfolio are no longer valuable for explaining the cross-section of IVs. However, we continue to estimate a positive and significant coefficient for *LOG_WTDDISP* (t-stat = 12.53) suggesting that the dispersion in patent values still retains its importance in explaining IV levels. Moreover, when adding the firm fixed effects in column (2), we find that all three of the patent portfolio variables are significant at traditional levels. This means that the patent portfolio valuation statistics still help to explain within-firm uncertainty levels, even after controlling for historical return volatility.

We next control for historical IV levels. We define *LOG_IMPVOLLAG1* (*LOG_IMPVOLLAG2*) as the natural log of the ATM IV from twelve (twenty-four) prior. Again, due to uncertainty persistence at the firm level, we expect to estimate positive associations between prior IV levels and current levels. Indeed, when adding the two new variables to the regressions as displayed in columns (3) and (4), we find the estimated coefficients are large and positive. However, qualitatively, the results when using the lagged IVs as controls are similar to those in columns (1) and (2). When we do not use the firm fixed effects in column (3), we only estimate a significant coefficient for *LOG_WTDDISP*. When including the firm fixed effects in column (4), however, we continue to find that three patent portfolio variables are significant at traditional levels and the estimate coefficients retain their original signs. Thus, even after controlling for prior uncertainty proxies in our regressions, we find evidence that firms' patent portfolio characteristics can help to explain the cross-section and within-firm measures of firm uncertainty.

In addition, because IVs are known to be biased related to subsequent realized volatilities (Carr and Wu 2009), we replicate our results when replacing the log IVs with the log of the daily realized volatility over the next month. When we replace the IVs with realized volatilities in Table 4, the regression results are qualitatively similar to those displayed. Specifically, we continue to estimate negative and significant coefficients for *LOG_PATNUM* across all the regressions, and we continue to estimate positive and significant coefficients for *LOG_PATVAL*, *LOG_PATWTDVAL*, *LOG_DISP*, and *LOG_WTDDISP*. Thus, our results are not due to factors that create systematic differences between options prices and actual volatility.

6. Additional analyses

6.1 Option market activity

As an additional analysis, we investigate option market activity as a function of our main patent portfolio variables. Prior studies have suggested that excess option market trading and option holdings are associated with either higher levels of private information or disagreements among investors (e.g., Roll et al. 2010; Choy and Wei 2012). In addition, perceived firm risk may also generate excess demand for hedging products. Thus, is possible that firms' patent portfolio characteristics influence investors' demand for option-based risk management strategies and the implicit leverage in options.

As a proxy of option market activity, we define the variable *LOG_OI* as the natural log of option open interest on the *IMPVOL* measurement date. For these tests, we include all options regardless of their strike price, their type (i.e., call or put), or their time-to-maturities. We display the regression results when using *LOG_OI* as the dependent variable in Table 8.

In column (1) we use our main dependent variables without the firm fixed effects. We find that the patent portfolio variables are strongly associated with the number of open option contracts. We estimate a positive coefficient for *LOG_PATWTDVAL* (*t*-stat = 22.09) and a negative coefficient for *LOG_PATNUM* (*t*-stat = 16.46). Similar to the results when explaining the cross-section of IVs, the regression results suggest offsetting effects for the number of patents and the value of the average patent in a firm's portfolio on option open interest. Moreover, we estimate a positive coefficient for *LOG_WTDDISP* (*t*-stat = 8.12). This suggests that when the average value of the patents becomes more dispersed investors tend to hold more option positions. We also note that our control variables generally obtain coefficients whose signs match prior studies. For example, we estimate a positive coefficient for firm size (*LOG_AT*) and a negative coefficient for the log book-to-market ratio (*LOG_BTM*) suggesting that open interest is conditionally higher for larger growth firms.

In column (2), we add *LOG_IMPVOL* as an additional control variable. Firms with more uncertainty likely generate more option activity and, as shown in the prior tables, our patent portfolio variables are associated with firm uncertainty levels. Consequently, the associations shown in column (1) may be explained by firm uncertainty levels. Indeed, we estimate a strong positive coefficient for *LOG_IMPVOL* (*t*-stat = 21.67) in column (2) indicating that option open interest is greater for firms with higher IVs. However, despite the inclusion of the new variable, we continue to estimate a strong negative coefficient for *LOG_PATNUM* and large positive coefficients for *LOG_PATWTDVAL* and

LOG_WTDDISP. In other words, the patent portfolio variables continue to explain the cross-section of open interest even conditional on the level of uncertainty.

We also consider that firms' patent portfolio characteristics generate additional trading activity across all markets and the change option market activity is not unique. Thus, in column (3) we add the control variable *LOG_STOCKVOLUME* defined as the log of average daily stock trading volume in shares for a firm over the prior three months. As expected, the estimated coefficient for *LOG_STOCKVOLUME* is strongly positive (*t*-stat = 46.43). This indicates that option open interest is conditionally higher when a firm has more equity market activity. However, the inclusion of the new variable does not alter our prior findings: firms' patent portfolio characteristics help to explain the level of open interest in the equity option market.

In columns (4) – (6) we repeat the analyses when adding firm fixed effects. The results are like those in columns (1) – (3). We again find that the number of patents in a firm's portfolio (*LOG_PATNUM*) is negatively associated with option open interest. Moreover, we estimate significant positive coefficients for the weighted total value of the patent portfolio (*LOG_PATWTDVAL*) and the dispersion of the values (*LOG_WTDDISP*). We thus conclude that the characteristics of firms' patent portfolios are strongly associated with option market activity and these relationships are found even when adjusting for stock market trading.

6.2 Put-to-call ratio

As a final test, we investigate if a firm's patent portfolio characteristics are related to its put-to-call open interest ratio. Puts generate downside risk protection and put prices are linked to the pricing of corporate debt (Cremers et al. 2008). Calls, on the other hand, are used by investors to bet on large price increases and, by using a covered call strategy, generate additional income (Israelov and Nielsen 2014). Given our previous results showing that firms' patent portfolio characteristics are related to investor uncertainty, it is likely that these factors are also related to investors' demand for downside versus upside price insurance.

To investigate this idea, we create the variable *LOG_PCOI* defined as the log ratio of put to call open interest at the end of the month. We then remove all observations where the put or call open interest is zero. We display the regression results in Table 9. In column (1) we use our standard set of independent variables without firm fixed effects. We find that the put-to-call ratio is positively related to the value of the patent portfolio (*LOG_PATWTDVAL*; *t*-stat = 1.99) but negatively related to the number of patents (*LOG_PATNUM*; *t*-stat = 3.40). Thus, the number of patents is associated with less put open interest compared to call open interest but the opposite is true for the total value of the patents. However, and perhaps somewhat surprisingly, the put-call open interest ratio is negatively related to *LOG_WTDDISP* (*t*-stat = 3.17). This seems to run counter to the risk arguments for the put-to-call ratio. We find that these results hold when also controlling for *LOG_IMPVOL* in column (2).

In columns (3) and (4) we add the firm fixed effects. We continue to find the put-to-call open interest ratio is negatively related to the number of patents in firms' patent portfolios, but the ratio is positively related to the total value of the portfolio. However, unlike the results in columns (1) and (2), we no longer estimate significant coefficients for *LOG_WTDDISP*. Thus, the dispersion of patent values does not influence the put-to-call open interest ratio when adjusting for firm-level unobserved heterogeneity. However, in total, the results of Table 9 show that firms' patent portfolio characteristics are associated with the number of puts held open relative to the number of calls.

7. Conclusion

Prior literature has shown the size of firms' patent portfolios, both in terms of the number of patents or its total size, is negatively related to factors such as cost of capital and other uncertainty proxies. In this paper, we extend this literature by considering the effect of a firm's patent portfolio composition on uncertainty measures. Drawing on basic portfolio theory for financial assets, we hypothesize that when analyzed together, the mean value of patents and the number of patents in the portfolio will have opposing signs. In addition, due to diversification effects, we also hypothesize that the dispersion of patent values in a firm's portfolio will be positively associated with uncertainty measures.

To test these hypotheses, we collect a large sample of short-term option IVs. We find that, as predicted, the number of patents in a firm's patent portfolio is negatively associated with IV levels. Conversely, conditional on the number of patents, we find that the mean value of patents and the dispersion of patent values are both positively associated with uncertainty levels. These findings are robust to controlling for other firm factors that have been shown to explain uncertainty levels across firms and the results hold when using firm fixed effects. Our results also show that forward-looking beta, systematic variance, and idiosyncratic variance are all associated with firms' patent portfolio characteristics. Finally, we find that these patent portfolio factors are strongly associated with option market activities and have some explanatory power for firms' put-to-call open interest ratios.

In short, this study provides strong evidence that firms' patent portfolios affect uncertainty levels. However, the relationship between firm uncertainty and firms' patent portfolios is not fully summarized by simple measures of portfolio size. Instead, the average value of patents and the number of patents have an offsetting effect on uncertainty levels and the concentration or spread of those values also impacts IVs. These results are important for future researchers who are interested in how patents affect firms' cost of capital and the cross-section of firm return volatilities.

References

Allison, J., Lemley, M., Moore, K., and Derek, R. (2004). Valuable patents. *Georgetown Law Journal* 92(3): 435–380.

Bena, J. and Garlappi, L. (2020). Corporate innovation and returns. *The Review of Corporate Finance Studies* 9(2): 340-383.

Bloom, N., Schankerman, M., and Van Reenen, J. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4): 1347-1393.

Callen, J., and Lyle, M. (2020). The term structure of implied costs of equity capital. *Review of Accounting Studies* 25: 342-404.

Cao, Y., Cheng, S., Tucker, J.W., and Wan, C. (2023). Technological peer pressure and skill specificity of job postings. *Contemporary Accounting Research* 40(3): 2106-2136.

Carr, P., and Wu, L. (2009). Variance risk premiums. *Review of Financial Studies* 22(3): 1311-1341.

Chambers, D., Jennings, R., and Thompson, R.B. (2002). Excess returns to R&D-intensive firms. *Review of Accounting Studies* 7(2-3): 133-158.

Choy, S., and Wei, J. (2012). Option trading: information or differences of opinion. *Journal of Banking and Finance* 36(8): 2299-2322.

Cremers, K.J.M., Driessen, J., and Maenhout, P. (2008). Explaining the level of credit spreads: Option-implied jump risk premia in a firm value model. *Review of Financial Studies* 21(5): 2209-2242.

Curtis, A., McVay, S., and Toynbee, S. (2020). The changing implications of research and development expenditures for future profitability. *Review of Accounting Studies* 25(2): 405-437

Eberhart, A., Maxwell, W., and Siddique, A. (2004). An examination of long-term abnormal stock returns and operating performance following R&D increases. *Journal of Finance* 59(2): 623-650.

Fama, E., and French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33(1): 3-56.

Glaeser, S., Michels, J., and Verrecchia, R. (2020). Discretionary disclosure and manager horizon: Evidence from patenting. *Review of Accounting Studies* 25(2): 597–635.

Hegde, S., and Mishra, D. (2023). Patented knowledge capital and implied equity risk premium. *Journal of Banking & Finance* 148: 106738.

Hirshleifer, D., Hsu, P., and Li, D. (2018). Innovative originality, profitability, and stock returns. *Review of Financial Studies* 31(7): 2553-2605.

Israelov, R., and Nielsen, L. (2014). Covered call strategies: One fact and eight myths. *Financial Analysts Journal* 70(6): 23-31.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics* 132 (2): 665-712.

Lemley, M. (2001). Rational ignorance at the Patent Office. *Northwestern University Law Review* 95(4): 1497–532.

Lemley, M., and Shapiro, C. (2005). Probabilistic patents. *Journal of Economic Perspectives* 19(2): 75–98.

Lev, B. (2018). Intangibles. Working paper, New York University, New York.

Lev, B., and Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of R&D. *Journal of Accounting and Economics* 21(1): 107-138.

Li, D. (2011). Financial constraints, R&D investment, and stock returns. *The Review of Financial Studies* 24(9): 2974-3007.

Lin, J., and Wang, Y. (2016). The R&D premium and takeover risk. *The Accounting Review* 91(3): 955-971.

Martens, T. (2021). The disclosure function of the U.S. Patent System: Evidence from the PTDL program and extreme snowfall. *Review of Accounting Studies* 28: 237-264.

Martin, I., and Wagner, C. (2019). What is the expected return on a stock? *Journal of Finance* 74(4): 1887-1929.

Neururer, T., Papadakis, G., and Riedl, E. (2016). Tests of investor learning models using earnings innovations and implied volatilities. *Review of Accounting Studies* 21: 400-437.

Neururer, T., Papadakis, G., and Riedl, E. (2020). The effect of reporting streaks on ex ante uncertainty. *Management Science* 66(8): 3771 – 3787.

Pastor, L., and Veronesi, P. (2003). Stock valuation and learning about profitability. *Journal of Finance* 58(5): 1749-1789.

Roll, R., Schwartz, E., and Subrahmanyam, A. (2010). O/S: The relative trading activity in options and stock. *Journal of Financial Economics* 96(1): 1-17.

Smith, K., and So, E. (2022). Measuring risk information. *Journal of Accounting Research* 60(2): 375-426.

Appendix. Variable Definitions

Dependent Variables

IMPVOL (*LOG_IMPVOL*)	The (natural log of the) mean of the 30-day 50 delta put and call implied volatilities measured on the last trading day of the calendar month.
IMPBETA	The option implied 30-day CAPM beta defined by the historical correlation between the stock and the CRSP value-weighted index times the ratio of *IMPVOL* divided by 1% of VIX index on the last trading day of the month. The historical correlation is measured over the last 91 calendar days using daily total returns.
LOG_IMPSYSVAR	The natural log of the option implied 30-day systematic return variance. Option implied systematic return variance is defined as the square of *IMPBETA* times the square of 1% of the VIX index.
LOG_IMPIDIOVAR	The natural log of option implied 30-day idiosyncratic return variance. Option implied idiosyncratic risk is defined as the square of *IMPVOL* minus the square of *IMPBETA* times the square of 1% of the VIX index.
LOG_OI	The natural log of the option open interest measured on the last trading day of the calendar month.
LOG_PC	The natural log of the put-to-call open interest measured on the last trading day of the calendar month.

Independent Variables

PATVAL *(LOG_PATVAL)*	The (natural log) of the number of patents in a firm's patent portfolio times the mean value (in millions of dollars) of the patents. The measurement time is the first day of the month where *IMPVOL* is measured. For a patent to be included in the firm's patent portfolio, the patent's issue date must be before the measurement date and the filing date must be less than twenty years in the past. We use the Kogan et al. (2017) method to determine patent values and we use real values for the patents adjusted to the year 1982.
PATNUM *(LOG_PATNUM)*	The (natural log) of the number of patents in a firm's patent portfolio. The measurement time is the first day of the month where *IMPVOL* is measured. For a patent to be included in the firm's patent portfolio, the patent's issue date must be before the measurement date and the filing date must be less than twenty years in the past.
LOG_PATWTDVAL	The natural log of the number of patents in a firm's patent portfolio times the discounted (weighted) mean value (in millions of dollars) of the patents. The measurement time is the first day of the month where *IMPVOL* is measured. For a patent to be included in the firm's patent portfolio, the patent's issue date must be before the measurement date and the filing date must be less than twenty years in the past. We use the Kogan et al. (2017) method to determine patent values and we use real values for the patents adjusted to the year 1982.
PAT_MEAN	The mean value in millions of dollar of the patents in the firm's patent portfolio. See the text and *PATVAL* for more information on how a patents value is estimated. Also see the description on *PATNUM* for more information on included patents.

PAT_STDEV	The standard deviation of the patent values for a firm's patent portfolio. See the description on *PATNUM* for more information on included patents.
PAT_WTDMEAN	The weighted mean value of the patents in the firm's patent portfolio. The weights are based a 15% discount function to the patent's value. The time for the discounting is the difference, in years, between the measurement date and the patent's filing date. See the description on *PATNUM* for more information on included patents.
PAT_WTDSTDEV	The weighted standard deviation of the value of the patents in the firm's patent portfolio. The weights are based a 15% discount function to the patent's value. The time for the discounting is the difference, in years, between the measurement date and the patent's filing date. See the description on *PATNUM* for more information on included patents.
LOG_DISP	The natural log of the ratio of *PAT_STDEV* to *PAT_MEAN*.
LOG_WTDDISP	The natural log of the ratio of *PAT_WTDSTDEV* to *PAT_WTDMEAN*.
RNDEXP (LOG_RNDEXP)	The (natural log) of total discounted quarterly R&D expenses over the prior twenty years plus one million dollars. R&D expenses are discounted at a rate of 15% per year. If the total discounted R&D expense is missing, the value set to one million dollars.
LOG_AT	The natural log of book assets in millions of dollars at the end of the prior quarter.
LOG_BTM	The natural log of book equity divided by stock capitalization at the end of the prior quarter.
LEV	Book liabilities divided by book assets at the end of the prior quarter.
ROA	Income before extraordinary items divided by book assets for the prior quarter.
LOSS	An indicator variable set to one if *ROA* < 0.
LOG_AGE	The (natural log of the) age of the firm in years on the *IMPVOL* measurement date. The first date for the firm is its first appearance in Compustat.
LOG_PATNUM60M	The (natural log) of the number of patents in a firm's patent portfolio over the prior 60 months. The measurement time is the first day of the month where *IMPVOL* is measured. For a patent to be included in the firm's patent portfolio, the patent's issue date must be before the measurement date and the filing date must be less than 60 months in the past.
LOG_PATVAL60M	The (natural log) of the number of patents in a firm's patent portfolio times the mean value (in millions of dollars) of the patents over the last 60 months. The measurement time is the first day of the month where *IMPVOL* is measured. For a patent to be included in the firm's patent portfolio, the patent's issue date must be before the measurement date and the filing date must be less than 60 months in the past.
LOG_DISP60M	The natural log of the ratio of patent values to mean value patent values for patents over the last 60 months.
LOG_HISTVOL	The natural log of dividend and split adjusted historical volatility over the prior 91 calendar days before the *IMPVOL* measurement.
LOG_IMPVOLLAG1 (LOG_IMPVOLLAG2)	The natural log of implied volatility measured one (two) years before the measurement date for *IMPVOL*.

Table 1. Sample selection

	Obs. Removed	Observations	Unique Firms
Monthly options data (2000-2017)		654,399	8,069
(-) Missing CRSP data	-86,851	567,548	7,044
(-) Missing Compustat data	-87,023	480,525	5,938
(-) OptionMetrics and CRSP price disagreement	-2,680	477,845	5,935
(-) Zero patents	-239,922	237,923	2,684
(-) Missing total patent value	-453	237,470	2,681
(-) Missing dispersion of patent values	-25,876	211,594	2,380
Final Sample		***211,594***	***2,380***

Notes: This table presents the sample selection process. OptionMetrics and CRSP price disagreements are instances where the log ratio of the option-implied ATM strike price and CRSP stock price were more than 10% in absolute value.

Table 2. Observation statistics

Panel A. Observations by year

Year	Observations	Firms	Median *PATNUM*
2000	9,326	983	24
2001	9,595	948	23
2002	10,001	969	26
2003	9,949	962	29
2004	11,011	1,048	29
2005	11,529	1,088	29
2006	11,933	1,131	30
2007	12,259	1,153	31
2008	11,979	1,132	34
2009	11,477	1,060	35
2010	11,969	1,110	38
2011	12,484	1,160	39
2012	12,659	1,160	40
2013	13,032	1,186	42
2014	13,419	1,204	42
2015	13,478	1,238	41
2016	13,084	1,189	41
2017	12,410	1,106	46

Panel B. Observations by Fama-French industries

Fama-French Industry	Description	Obs.	Firms	Median *PATNUM*
1	Consumer Nondurables	9,565	90	31
2	Consumer Durables	8,689	79	97
3	Manufacturing	30,576	310	66
4	Oil, Gas, & Coal	6,171	57	33
5	Chemicals and Allied Products	8,566	73	202
6	Business Equipment	68,109	822	47
7	Telephone and Television Transmission	5,064	61	41
8	Utilities	5,251	44	7
9	Wholesale, Retail, and Some Services	7,735	74	6
10	Healthcare, Medical Equipment, and Drugs	38,530	520	34
11	Finance	9,651	93	11
12	Other	13,687	157	9

Notes: This table provides sample statistics. Panel A shows the number of monthly observations, the number of unique firms represented in each year, and the number of median patents held by the firms. In Panel B, we display the information by Fama-French 12 industries.

Table 3. Summary statistics and correlations

Panel A. Summary statistics

	Q1	Mean	Median	Q3	Stdev
LOG_IMPVOL	-1.272	-0.916	-0.930	-0.572	0.495
LOG_PATVAL	3.545	5.551	5.249	7.322	2.678
LOG_PATNUM	2.079	3.790	3.526	5.198	2.094
LOG_DISP	0.117	0.529	0.471	0.843	0.645
LOG_RNDEXP	2.817	4.305	4.750	6.037	2.700
LOG_AT	5.911	7.475	7.279	8.863	2.061
LOG_BTM	-1.487	-1.045	-0.971	-0.501	0.788
LEV	0.278	0.467	0.472	0.636	0.230
ROA	-0.001	0.002	0.011	0.022	0.045
LOSS	0.000	0.264	0.000	1.000	0.441
LOG_AGE	8.291	8.853	8.850	9.562	0.776

Panel B. Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
LOG_IMPVOL	(1)	**1.000**	**-0.363**	**-0.246**	**-0.079**	**-0.048**	**-0.602**	**0.014**	**-0.317**	**-0.403**	**0.449**	**-0.469**
LOG_PATVAL	(2)	**-0.361**	**1.000**	**0.875**	**-0.454**	**0.576**	**0.620**	**-0.105**	**0.217**	**0.188**	**-0.184**	**0.354**
LOG_PATNUM	(3)	**-0.225**	**0.860**	**1.000**	**-0.530**	**0.678**	**0.364**	**-0.072**	**0.088**	**0.128**	**-0.114**	**0.319**
LOG_DISP	(4)	**-0.097**	**-0.440**	**-0.519**	**1.000**	**-0.405**	**-0.034**	**0.035**	**0.113**	**0.025**	**-0.064**	**-0.074**
LOG_RNDEXP	(5)	**-0.113**	**0.628**	**0.685**	**-0.419**	**1.000**	**0.106**	**-0.182**	**-0.110**	**0.019**	**0.021**	-0.001
LOG_AT	(6)	**-0.621**	**0.614**	**0.318**	**-0.036**	**0.213**	**1.000**	**0.158**	**0.534**	**0.328**	**-0.356**	**0.462**
LOG_BTM	(7)	**0.038**	**-0.102**	**-0.086**	**0.036**	**-0.185**	**0.130**	**1.000**	**-0.134**	**0.027**	0.000	**0.123**
LEV	(8)	**-0.328**	**0.221**	**0.069**	**0.119**	**-0.039**	**0.549**	**-0.072**	**1.000**	**0.069**	**-0.135**	**0.353**
ROA	(9)	**-0.372**	**0.194**	**0.149**	**0.008**	**0.105**	**0.244**	**-0.244**	**-0.027**	**1.000**	**-0.687**	**0.249**
LOSS	(10)	**0.450**	**-0.185**	**-0.103**	**-0.069**	**-0.011**	**-0.372**	**0.027**	**-0.138**	**-0.764**	**1.000**	**-0.299**
LOG_AGE	(11)	**-0.475**	**0.342**	**0.295**	**-0.058**	**0.050**	**0.492**	**0.115**	**0.365**	**0.207**	**-0.296**	**1.000**

Notes: This table presents the summary statistics and correlation matrix. Panel A shows the sample summary statistics. Panel B shows the correlation matrix. For the correlation matrix, the upper-right portion shows the Pearson correlations and the bottom-left shows the Spearman correlations. Correlations in bold are significant at the 1% level, two-sided tests. All statistics are calculated after winsorizing the variables at the 1^{st} and 99^{th} percentiles. See the Appendix for variable definitions.

Table 4. Portfolio value, patent number, and value precision

	Dependent Variable = *LOG_IMPVOL*							
	(1)		(2)		(3)		(4)	
LOG_PATVAL	**0.032**	**(2.32**)**	**0.180**	**(6.99***)**				
LOG_PATWTDVAL					**0.050**	**(3.38***)**	**0.230**	**(11.08***)**
LOG_PATNUM	**-0.045**	**(3.58***)**	**-0.187**	**(8.96***)**	**-0.045**	**(3.50***)**	**-0.204**	**(11.63***)**
LOG_DISP	**0.052**	**(12.87***)**	**0.025**	**(4.90***)**				
LOG_WTDDISP					**0.051**	**(14.22***)**	**0.020**	**(5.73***)**
LOG_RNDEXP	0.008	(1.17)	-0.056	(3.22***)	0.006	(0.81)	-0.060	(3.38***)
LOG_AT	-0.252	(25.44***)	-0.245	(16.84***)	-0.265	(24.21***)	-0.277	(18.21***)
LOG_BTM	0.056	(10.99***)	0.055	(11.57***)	0.055	(10.67***)	0.060	(12.32***)
LEV	0.047	(9.14***)	0.079	(15.37***)	0.044	(8.45***)	0.081	(15.72***)
ROA	-0.048	(14.10***)	-0.011	(5.48***)	-0.047	(13.49***)	-0.010	(5.15***)
LOSS	0.145	(21.14***)	0.055	(13.44***)	0.145	(20.54***)	0.055	(12.68***)
LOG_AGE	-0.085	(15.98***)	0.025	(1.54)	-0.085	(15.22***)	0.018	(1.08)
Adj. R^2	70.2%		81.8%		71.1%		81.8%	
N	211,594		211,594		190,598		190,598	
Industry ´ Month FE	Yes		Yes		Yes		Yes	
Firm FE	No		Yes		No		Yes	

Notes: This table presents the main regression results when also including the patent precision variables as independent variables. The first value is the estimated regression coefficient and the second value in the parentheses is the associated *t*-statistic. Industries are defined by two-digit SIC codes. ***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels using two-sided tests. All regressions are estimated after winsorizing the variables at the 1st and 99th percentiles. Standard errors are clustered at the month and firm levels. See the Appendix for variable definitions.

Table 5. Patents granted in the past five years.

	Dependent Variable = *LOG_IMPVOL*	
	(1)	(2)
LOG_PATVAL60M	**0.060 (3.97***)**	**0.200 (13.63***)**
LOG_PATNUM60M	**-0.048 (3.91***)**	**-0.168 (14.30***)**
LOG_DISP60M	**0.045 (12.60***)**	**0.023 (8.41***)**
LOG_RNDEXP	0.012 (1.69*)	-0.057 (3.28***)
LOG_AT	-0.278 (22.10***)	-0.310 (18.07***)
LOG_BTM	0.061 (10.65***)	0.069 (13.67***)
LEV	0.043 (7.34***)	0.086 (15.99***)
ROA	-0.048 (12.89***)	-0.009 (4.51***)
LOSS	0.149 (19.21***)	0.053 (11.44***)
LOG_AGE	-0.082 (14.61***)	0.012 (0.81)
Adj. R^2	71.5%	82.9%
N	157,064	157,064
Industry × Month FE	Yes	Yes
Firm FE	No	Yes

Notes: This table presents the regression results when limiting the patents to those issued and whose filing date is less than 60 months from the implied volatility measurement date. The first value is the estimated regression coefficient and the second value in the parentheses is the associated *t*-statistic. Industries are defined by two-digit SIC codes. ***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels using two-sided tests. All regressions are estimated after winsorizing the variables at the 1st and 99th percentiles. Standard errors are clustered at the month and firm levels. See the Appendix for variable definitions.

Table 6. Implied beta, implied systematic variance, and implied idiosyncratic variance

	Dependent Variable:					
	IMPBETA		*LOG_IMPSYSVAR*		*LOG_IMPIDIOVAR*	
	(1)	(2)	(3)	(4)	(5)	(6)
LOG_PATWTDVAL	**0.106 (5.34***)**	**0.235 (6.01***)**	**0.185 (4.14***)**	**0.355 (4.77***)**	**0.085 (2.58**)**	**0.465 (11.02***)**
LOG_PATNUM	**-0.092 (5.49***)**	**-0.208 (6.43***)**	**-0.153 (4.23***)**	**-0.342 (5.63***)**	**-0.085 (2.85***)**	**-0.419 (11.56***)**
LOG_WTDDISP	**0.051 (8.56***)**	**0.013 (2.11**)**	**0.086 (7.36***)**	**0.018 (1.42)**	**0.109 (13.68***)**	**0.046 (6.10***)**
LOG_RNDEXP	0.004 (0.37)	-0.083 (3.35***)	0.001 (0.05)	-0.164 (3.13***)	0.021 (1.45)	-0.114 (2.97***)
LOG_AT	-0.135 (9.22***)	-0.045 (1.66*)	-0.212 (6.57***)	0.031 (0.57)	-0.614 (25.68***)	-0.660 (20.07***)
LOG_BTM	0.011 (1.13)	-0.033 (3.00***)	0.014 (0.71)	-0.088 (4.05***)	0.129 (11.88***)	0.159 (16.79***)
LEV	0.012 (1.38)	0.007 (0.69)	0.011 (0.59)	-0.025 (1.29)	0.103 (9.03***)	0.198 (18.49***)
ROA	-0.022 (3.89***)	0.004 (0.96)	-0.025 (2.18**)	0.015 (1.68*)	-0.093 (12.24***)	-0.019 (4.48***)
LOSS	0.129 (10.95***)	0.069 (8.54***)	0.213 (8.69***)	0.118 (6.87***)	0.328 (20.68***)	0.114 (11.95***)
LOG_AGE	-0.047 (6.16***)	0.018 (0.59)	-0.085 (5.08***)	0.032 (0.49)	-0.206 (16.22***)	0.052 (1.43)
Adj. R^2	31.0%	81.8%	40.8%	52.4%	69.9%	81.3%
N	190,596	190,596	190,571	190,571	190,571	190,571
Industry × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes

Notes: This table presents the regression results when using implied beta, log implied systematic, and log implied idiosyncratic variance as the dependent variables. The first value is the estimated regression coefficient and the second value in the parentheses is the associated *t*-statistic. Industries are defined by two-digit SIC codes. ***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels using two-sided tests. All regressions are estimated after winsorizing the variables at the 1st and 99th percentiles. Standard errors are clustered at the month and firm levels. See the Appendix for variable definitions.

Table 7. Robustness tests – control for lagged uncertainty

	Dependent Variable = *LOG_IMPVOL*			
	(1)	(2)	(3)	(4)
LOG_PATWTDVAL	**0.006 (0.81)**	**0.129 (9.58***)**	**0.002 (0.30)**	**0.117 (9.12***)**
LOG_PATNUM	**-0.008 (1.11)**	**-0.118 (10.10***)**	**-0.002 (0.35)**	**-0.107 (9.16***)**
LOG_WTDDISP	**0.025 (12.53***)**	**0.011 (4.59***)**	**0.011 (6.96***)**	**0.006 (2.45**)**
LOG_RNDEXP	0.005 (1.43)	-0.040 (3.69***)	0.002 (0.83)	-0.035 (3.27***)
LOG_AT	-0.139 (20.73***)	-0.202 (19.01***)	-0.077 (15.36***)	-0.147 (14.71***)
LOG_BTM	0.034 (12.35***)	0.048 (15.09***)	0.030 (13.90***)	0.042 (13.49***)
LEV	0.024 (8.71***)	0.056 (16.48***)	0.020 (9.41***)	0.044 (13.94***)
ROA	-0.028 (12.61***)	-0.007 (4.43***)	-0.013 (8.33***)	-0.006 (4.17***)
LOSS	0.074 (18.18***)	0.038 (12.15***)	0.053 (15.66***)	0.035 (11.44***)
LOG_AGE	-0.038 (12.63***)	0.031 (2.71***)	-0.020 (9.66***)	0.048 (4.31***)
LOG_HISTVOL	0.280 (69.28***)	0.197 (46.84***)	0.224 (60.93***)	0.182 (45.56***)
LOG_IMPVOLLAG1			0.098 (36.40***)	0.060 (24.62***)
LOG_IMPVOLLAG2			0.056 (23.14***)	0.024 (10.96***)
Adj. R^2	81.6%	85.3%	83.3%	85.4%
N	190,597	190,597	163,665	163,665
Industry × Month FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes

Notes: This table presents the regression results explaining implied volatilities when using lagged historical volatilities and lagged implied volatilities as controls. The first value is the estimated regression coefficient and the second value in the parentheses is the associated *t*-statistic. Industries are defined by two-digit SIC codes. ***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels using two-sided tests. All regressions are estimated after winsorizing the variables at the 1st and 99th percentiles. Standard errors are clustered at the month and firm levels. See the Appendix for variable definitions.

Table 8. Option open interest

	Dependent Variable = *LOG_OI*					
	(1)	(2)	(3)	(4)	(5)	(6)
LOG_PATWTDVAL	**2.037 (22.09***)**	**1.962 (21.55***)**	**0.493 (6.45***)**	**1.054 (9.25***)**	**0.923 (8.28***)**	**0.323 (3.56***)**
LOG_PATNUM	**-1.322 (16.46***)**	**-1.254 (16.11***)**	**-0.336 (5.30***)**	**-0.667 (7.18***)**	**-0.550 (6.10***)**	**-0.164 (2.27**)**
LOG_WTDDISP	**0.201 (8.12***)**	**0.124 (5.32***)**	**0.050 (2.78***)**	**0.104 (4.98***)**	**0.092 (4.54***)**	**0.057 (3.54***)**
LOG_RNDEXP	0.065 (1.55)	0.056 (1.43)	-0.010 (0.32)	-0.135 (1.40)	-0.100 (1.11)	-0.017 (0.25)
LOG_AT	0.766 (11.61***)	1.167 (16.76***)	0.283 (4.76***)	1.378 (17.30***)	1.536 (19.62***)	0.752 (11.45***)
LOG_BTM	-0.470 (15.92***)	-0.553 (19.84***)	-0.270 (11.50***)	-0.379 (17.79***)	-0.413 (19.86***)	-0.184 (11.20***)
LEV	-0.245 (7.20***)	-0.313 (9.69***)	-0.166 (6.37***)	-0.125 (5.11***)	-0.171 (7.15***)	-0.059 (2.93***)
ROA	-0.164 (7.99***)	-0.093 (5.07***)	-0.063 (4.27***)	-0.031 (2.76***)	-0.025 (2.28**)	-0.027 (2.77***)
LOSS	0.439 (9.99***)	0.220 (5.65***)	0.174 (5.82***)	0.039 (1.90*)	0.008 (0.40)	0.025 (1.53)
LOG_AGE	-0.133 (3.78***)	-0.005 (0.16)	0.052 (2.12**)	0.193 (1.89*)	0.182 (1.83*)	0.086 (1.10)
LOG_IMPVOL		0.754 (21.67***)	0.175 (6.71***)		0.285 (13.77***)	0.027 (1.79*)
LOG_STOCKVOLUME			1.548 (46.43***)			1.308 (46.35***)
Adj. R^2	60.8%	64.1%	76.5%	84.7%	85.0%	88.3%
N	190,598	190,598	190,597	190,598	190,598	190,597
Industry × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes

Notes: This table presents the regression results when using log open interest as the dependent variable. The first value is the estimated regression coefficient and the second value in the parentheses is the associated *t*-statistic. Industries are defined by two-digit SIC codes. ***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels using two-sided tests. All regressions are estimated after winsorizing the variables at the 1st and 99th percentiles. Standard errors are clustered at the month and firm levels. See the Appendix for variable definitions.

Table 9. Market demand for downside risk protection – put-to-call ratios

	Dependent Variable = *LOG_PCOI*			
	(1)	(2)	(3)	(4)
LOG_PATWTDVAL	**0.053 (1.99**)**	**0.058 (2.18**)**	**0.151 (2.87***)**	**0.156 (2.96***)**
LOG_PATNUM	**-0.077 (3.40***)**	**-0.081 (3.60***)**	**-0.114 (2.72***)**	**-0.118 (2.81***)**
LOG_WTDDISP	**-0.028 (3.17***)**	**-0.023 (2.62***)**	**0.012 (1.10)**	**0.012 (1.14)**
LOG_RNDEXP	-0.021 (1.45)	-0.020 (1.43)	-0.140 (3.47***)	-0.142 (3.49***)
LOG_AT	0.262 (12.90***)	0.236 (11.12***)	0.519 (12.44***)	0.513 (12.25***)
LOG_BTM	-0.097 (9.65***)	-0.092 (9.14***)	-0.108 (9.79***)	-0.107 (9.65***)
LEV	-0.066 (6.08***)	-0.062 (5.73***)	-0.051 (3.89***)	-0.049 (3.73***)
ROA	0.043 (5.15***)	0.039 (4.63***)	-0.003 (0.44)	-0.003 (0.47)
LOSS	-0.006 (0.33)	0.009 (0.49)	0.019 (1.33)	0.020 (1.42)
LOG_AGE	0.024 (2.20**)	0.015 (1.41)	-0.045 (1.11)	-0.045 (1.10)
LOG_IMPVOL		-0.049 (4.37***)		-0.010 (1.13)
Adj. R^2	10.4%	10.5%	26.7%	26.7%
N				
Industry × Month FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes

Notes: This table presents the regression results when using log put to call open interest as the dependent variable. The first value is the estimated regression coefficient and the second value in the parentheses is the associated *t*-statistic. *N* = 188,531 for all regressions. Industries are defined by two-digit SIC codes. ***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels using two-sided tests. All regressions are estimated after winsorizing the variables at the 1st and 99th percentiles. Standard errors are clustered at the month and firm levels. See the Appendix for variable definitions.