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Information Ambiguity, Patents and the Market Value of Innovative Assets[1]

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Abstract

Research and development (R&D) is often essential for firms' profitability and growth. At the same time, R&D is long-term and risky. We show that innovation activities lead to information ambiguity about the future value of firm's assets. This effect appears to be more pronounced for small and less reputed firms. Information ambiguity further lowers firms' market value and, in particular, the market value of innovative assets. We further show that high quality patents mitigate the negative effect of information ambiguity to some extent.

Keywords: R&D, patents, information ambiguity, market value

JEL-Classification: G10, G14, D81, O34

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1. Introduction

The past decades have seen a persistent upward trend in corporate research and development (R&D) (Bates et al., 2009; Brown et al., 2009). Investment in R&D can increase firms' profitability, growth and market value (Demsetz, 1988; Griliches, 1981; Hall et al., 2005). For this reason, R&D is an important strategic source for achieving a competitive advantage vis-à-vis competitors (Grant, 1996a; Kogut and Zander, 1992; Nonaka, Toyama and Nagata, 2000). Positive returns to R&D investments can, however, not be taken for granted because R&D is risky and progress is more erratic than with standard investments (Holmstrom, 1989: 311). Furthermore, R&D projects are long-term, R&D investments are irreversible and sunk, and R&D outcomes are uncertain and intangible (Czarnitzki and Toole, 2009).

These features of R&D put outside investors in a situation where the information they receive about firms' innovation activities - by analysts and the firm itself - is ambiguous. Information is ambiguous when its quality as a signal to the market is uncertain (Epstein and Schneider, 2008) and when its implications for the market valuation of a firm's assets are uncertain (Zhang, 2006). Information ambiguity is clearly distinct from risk as ambiguity describes uncertainty about the probabilities over payoffs whereas risk defines uncertainty over payoffs (Williams, 2015). Investors receive information from the firm related to its innovation activities, but it is unclear whether this information is complete and reliable (Bhattacharya and Ritter, 1983; Anton and Yao, 1998) because firms tend to withhold or selectively present information about innovation projects and their progress for strategic reasons.[2]

[2] Sharing information about innovation projects can threaten a firm's competitive advantage vis-à-vis market rivals because competitors that learn early about the focal firm's ongoing and future innovations can proactively prepare a strategic response (Horstman et al., 1985, Anton and Yao, 2004).

This paper explores the role of information ambiguity surrounding the innovative assets of firms. Ambiguous information as information with uncertain implications for the market valuation of a firm's assets (Zhang, 2006) is extensively discussed in the financial literature (e.g. French and Poterba, 1991, Garlappi et al., 2007, Peijnenburg, 2014, Dimmock et al. 2013). This literature establishes that investors tend to be inherently ambiguity averse so that they require a compensation for holding ambiguous assets (Epstein and Schneider, 2008).

While there is already a well-established literature on the market value of innovative assets (Griliches, 1981, Hall et al., 2000, see Czarnitzki et al, 2006, for a survey) as well as on information ambiguity (e.g. French and Poterba, 1991, Garlappi et al., 2007, Peijnenburg, 2014, Dimmock et al. 2013), here we explicitly investigate the relationship between information ambiguity and the value of innovative assets. Due to their distinct features, innovative assets are prone to information ambiguity and deserve a separate investigation. We further investigate high quality patents as an R&D-specific means to counteract negative implications of information ambiguity.

We provide an empirical analysis of the relationship between R&D, information ambiguity and the valuation of firms' innovative assets for a panel of U.S. manufacturing firms. We proceed in two steps. First, we show that R&D investment increases information ambiguity about the firm's assets. We use analyst forecast dispersion as a widely accepted measure of information ambiguity, parameter risk, or estimation risk (e.g. Anderson et al., 2005, 2009; Doukas et al., 2006; Dittmar and Thakor, 2007; Erickson et al., 2012; Güntay and Hackbarth, 2010; Johnson, 2004; Kumar et al., 2008). Second, we study the impact of information ambiguity on the market value of firms by estimating hedonic market value regressions (Griliches, 1981; Hall, 2000). Our analysis reveals that information ambiguity about the firm's future profits increases with firms' R&D activities and that information ambiguity reduces the market value of firms and of their innovative assets in particular. We further show that high quality patents mitigate the negative effect to some extent. This suggests that high quality patents carry information that outsiders to the firm rely on to some extent.

Our study offers important contributions. We illustrate the importance of information ambiguity for the value of R&D. By showing a negative effect of information ambiguity on the market valuation of firm's innovative assets, we also contribute to a small, but developing literature on the effects of information ambiguity for the evaluation of innovative assets (Thomas, 2002; Gu and Wang, 2005).

The finding that knowledge assets receive a lower market valuation in the presence of information ambiguity puts firms in the difficult position to decide for disclosure mechanisms to reduce information ambiguity (e.g. Lev, 2001; Jones, 2007) at the cost of sharing valuable information and potentially foregoing a competitive advantage. As we establish that high quality patents mitigate the negative effect of information ambiguity on innovative assets we show that a good intellectual property management can to some extent work towards a solution.

The remainder of the paper is organized as follows. The next section develops a theoretical framework from which hypotheses are derived. Section 3 outlines our empirical approach. Section 4 introduces the sample and defines the variables used for the empirical analysis presented in section 5. The last section concludes with a discussion of our findings and managerial implications.

2. Theoretical framework and hypotheses

Information is ambiguous if the probabilities that certain states will occur in the future are unknown. With imprecise information, individuals consider several probability measures without knowing which of these measures is correct. The lack of knowledge about underlying probabilities is called ambiguity (Ellsberg, 1961). The concept of ambiguity goes back to Knight (1921) and Keynes (1921) and is a clearly distinct concept from risk. An outcome is risky if the probabilities that certain states will occur in the future are precisely known, e.g. in a fair roulette game. An outcome is ambiguous if these probabilities are unknown.

Most applications of the concept of information ambiguity can be found in the theoretical literature on financial markets (e.g. Epstein and Wang, 1994; Epstein and Schneider, 2008; Illeditsch, 2011; Easley et al., 2014; Garlappi et al., 2007, see Etner et al., 2012, for a recent survey). Empirical research in this field is mostly experimental (Bossaerts et al., 2010). Among the studies that use actual data to analyze the role and implications of information ambiguity we find Kumar et al. (2008), Anderson et al. (2005), Doukas et al. (2006) and Dittmar and Thakor (2007). These studies show that information ambiguity matters for asset pricing. Anderson et al. (2005), for instance, show that forecast dispersion is a priced risk factor in traditional asset pricing models. Dittmar and Thakor (2007) suggest that stock prices are depressed when forecast dispersion is high. We contribute to the scarce empirical evidence providing an analysis of the relationship between R&D and information ambiguity.

2.1. R&D and information ambiguity

Information ambiguity is prevalent when the quality of available information is poor. A typical example for a poor information environment is a firm investing in R&D. R&D is both risky and surrounded by information ambiguity. The risk factor stems from the typical characteristics of R&D such as technological and market uncertainty (Toole and Czarnitzki, 2011) as well as its intangibility and associated appropriation problems due to externalities (Arrow, 1962). These factors are related to risk since different outcomes can be associated to a certain probability, e.g. a technological feasibility study can attach probabilities to the chance of success of innovative projects. Due to the risks associated with R&D outside investors have more difficulties to distinguish profitable R&D projects from less profitable ones than better informed corporate insiders (Leland and Pyle, 1977).

R&D is also characterized by information ambiguity for the investor. Corporate insiders have better knowledge about their innovative projects and their success prospects than outsiders to the firm

(Aboody and Lev, 2000). Firms have strong incentives to keep their knowledge about their R&D private in order to extract as much value as possible through the exploitation of first-mover advantages (Nelson, 1990). If they disclosed such knowledge, "…any one purchaser can destroy the owner's monopoly, since he can reproduce the information at little or no cost" (Arrow, 1962: 615). The thread of imitation is a substantial cost of information disclosure feeding the market's doubts about the quality of signals regarding R&D projects (Bhattacharya and Ritter, 1983; Anton and Yao, 1998; Hall et al., 2014). Strategic non-disclosure as well as the facts that R&D expenditures are immediately expensed and that balance sheets do not report the R&D capital of a firm puts investors in a situation of a poor quality information environment (Aboody and Lev, 2000; Chan et al., 2001; Lev, 2001; Lev and Sougiannis, 1996; Lev et al., 2005).

H1: *R&D investment increases information ambiguity about the firm's assets.*

Information ambiguity is expected to vary with the quality of the information environment. Firms in a poor information environment such as, for instance, small firms and firms that lack a strong reputation should face a higher level of information ambiguity. The association between R&D investment and information ambiguity should be stronger for these firms. Larger firms are, in contrast, associated with lower information ambiguity since there is more information available about firms beyond a specific size threshold and information about large firms is easier to acquire (Thomas, 2002). Similarly, information about firms which are less reputable is more difficult to gather and to judge (Diamond, 1989).

H1a: *R&D investment increases information ambiguity about the firm's assets more for small firms.*

H1b: *R&D investment increases information ambiguity about the firm's assets more for firms lacking a strong reputation.*

2.2. Information ambiguity and the market value of innovative assets

Information ambiguity affects investors' decisions. If there is no precise information investors have to form beliefs about the outcome probabilities on which they base their decisions. A pessimistic investor bases her decisions on lower values than her actual expectations in order to account for information ambiguity. Therefore, the investor would need to be compensated for accepting a deal under information ambiguity, on top of a potential compensation for risk (Epstein and Schneider, 2008).

Consider an investor facing the decision to invest in an innovating firm A or to invest in a firm B that does not conduct R&D. The expected net gain of an investment in firm B would be zero (no ambiguity) with a certain variance (risk). In case of the innovating firm A the investor expects ambiguous information which means that the expected net gain correlates with factors which are unobservable to him. In this case, the expected net gain from the investment is a function of the unknown true expected value of the firms' assets (ambiguity) with some variance (risk) conditional on that mean. The set of subjective beliefs about the expected gain has expanded from a point (zero) to a range over which the probabilistic distribution is defined. This range reflects the loss of confidence in the expected return to investment. As a result, an ambiguity averse investor requires an ambiguity compensation for her investment (on top of an ordinary risk premium). The ambiguity premium becomes visible as a discount on the current value of the firm's assets.

Multiple evidence shows that investors behave ambiguity averse. Hsu et al. (2005) and Levy et al. (2010) argue that ambiguity aversion is rooted in the fundamentals of human cognition. Several studies provide experimental evidence following Ellberg's (1961) pioneering study (see Camerer and Weber, 1992, and Keren and Gerritsen, 1999, for surveys). Early empirical evidence for investors behaving ambiguity avers has been provided by French and Poterba (1991) who show that investors sacrifice 3% of expected annual revenue by holding too many shares of domestic firms and too few shares of foreign firms. A likely explanation is that investors believe that they have better information about domestic firms and more trust in this information, i.e. they face less information ambiguity, so that they require a smaller ambiguity premium. More recently, Garlappi et al. (2007), Peijnenburg (2014) and Dimmock et al. (2013) showed that ambiguity aversion also reduces the fraction of financial wealth allocated to equity.

Empirical evidence also confirms that the market underreacts to R&D. A firm's future returns to R&D tend to be higher compared to what the firm's current market value suggests. For instance, Lev and Sougiannis (1996) document substantial excess returns for R&D intensive firms. Chan et al. (2001) find significant abnormal stock returns for a sample of R&D intensive firms with poor historical stock performance. Penman and Zhang (2002) document positive impacts of changes in R&D investment and future stock returns. Similarly, Eberhart et al. (2004) find significant abnormal returns to unexpected R&D increases. They conclude that unexpected R&D increases lead to mispricing that the market takes years to correct. Finally, Daniel and Titman (2006) decompose stock returns into a tangible and an intangible component finding that intangibles predict future stock returns whereas tangible returns do not. Part of the explanation for this phenomenon is that investors require compensation for bearing the uncertainty that comes along with R&D (Chambers et al., 2002; Lev and Sougiannis, 1996). We hypothesize that abnother part of this effect is explained by information ambiguity.

H2: *Information ambiguity decreases the market value of firms' assets and in particular the market value of firms' innovative assets.*

2.3. Patents, information ambiguity and the market value of innovative assets

Prior literature has shown that patents can spur R&D investment and reduce market uncertainty (Czarnitzki and Toole, 2011). Patents may also serve as a means to reduce information ambiguity because they may affect market participants' beliefs about the future returns to R&D in two ways. First, patents serve as a proof of concept providing codified information about the nature of the patented invention thereby informing investors about firms' R&D projects (Cohen et al., 2000; Long, 2002). In other words, patents may reduce information ambiguity about the type of R&D that a firm is conducting. Second, patents can serve as signals of firms' own expectations about the quality of their R&D projects (Bhattacharya and Ritter, 1983; Gans, Hsu and Stern, 2008; Häussler et al., 2008). Griliches (1990) points out that in theory, firms only apply for patent protection when the expected future returns exceed the costs of patenting. Similarly, Hall et al. (2005) argue that a successful patent application indicates that a firm does not expect an R&D project to be a 'dry hole' from which it does not expect any future profits. Assuming that patents provide information about R&D quality, patents reduce market participants' perceived risk of negative R&D outcomes.

It is, however, also well documented that the quality distribution of patents is highly skewed with the majority of patents having no value and a handful of patents being responsible for the largest share of the value (Scherer, 1965, Pakes and Schankerman, 1984, Pakes, 1986, Griliches, 1990, Harhoff et al., 1999, Hall et al., 2005, Silverberg and Verspagen, 2007). Patent value is often proxied by the citations that patents receive by future patent applications. Patent citations have been shown to correlate with the economic value of patents (Hall et al., 2005), with the evaluation of the technology according to peers (Albert et al., 1991) and with the social value of the invention (Trajtenberg, 1990). They reflect the skewness of the patent value distribution. With focus on publicly listed U.S. firms, Hall et al. (2005), for instance, find that one quarter of the one million patents in their data received no citations by later patents, 150,000 received only one and just four received more than 200 citations.

While patents are proofs of concept, they say nothing about the importance or the value of the technology. Patent citations can add this information. Since citations are public information, they can help outsiders to form an opinion about the value or the importance of firms' individual patents and patent stock. This implies that patent citations reduce information ambiguity. Patents receiving zero citations only reduce information ambiguity to the extent that outsiders learn which technologies a firm is working on and it is questionable to which extent this information is new to the market. Hence, we hypothesize that only high quality patents are likely to reduce information ambiguity by 'cutting off' the left tail of the distribution of market participants' expected future returns to R&D. This leads us to the third hypothesis:

H3: *High quality patents mitigate the negative effect of information ambiguity on firms' market value.*

3. Empirical approach

3.1. Hypothesis 1

The test of the first hypothesis is straightforward. We employ cross-sectional OLS (where we simply pool all our observations) and fixed-effects panel regressions (where we allow for a firm specific unobservable effect) in order to investigate the impact of R&D expenditure on information ambiguity. Information ambiguity is proxied by analyst forecast dispersion following prior studies (Anderson et al., 2005, 2009; Doukas et al., 2006; Dittmar and Thakor, 2007; Erickson et al., 2012; Güntay and Hackbarth, 2010; Johnson, 2004; Kumar et al., 2008).

3.2. Hypotheses 2 and 3

In order to test hypotheses 2 and 3 we employ a market value approach (Griliches, 1981; Hall, 2000; Hall et al., 2005; Oriani and Sobrero, 2008). The market value approach draws from the hedonic pricing model which views firms as bundles of their assets. The market value approach assumes that financial markets assign a value to the firms' asset bundles that is equal to the present discounted value of their future cash flows. A large body of literature shows that R&D and other measures of knowledge assets positively correlate with market value as measured by Tobin's q (Cockburn and Griliches, 1988; Griliches, 1981; Hall, 2005; Hall et al., 2005; Pakes and Schankerman, 1984; see Czarnitzki et al., 2006, for a survey).

Following most existing studies we assume a linear market value equation with firm assets entering additively. This leads to the following equation, with A representing the physical assets and K the knowledge assets of firm *i* at time *t*, i.e. firms' R&D and (citation-weighted) patent stock (Hall et al., 2005).

$$V_{it}(A_{it}, K_{it}) = q(A_{it} + \gamma K_{it})^{\sigma} \tag{1}$$

Under the assumption that there is information ambiguity about the firms' assets δ_{it} the investor cannot perfectly judge the market value of firms' assets and adds an information ambiguity discount:[3]

$$\widetilde{V}_{it}(A_{it}, K_{it}) = \exp(\delta_{it})\, q(A_{it} + \gamma K_{it})^{\sigma} \tag{2}$$

Under constant returns to scale ($\sigma = 1$) and by dividing both sides of the equation by A and taking logs equation (2) can be rewritten as:

$$\log q_{it} = \log \frac{\widetilde{V}_{it}}{A_{it}} = \delta_{it} + \log q + \log(1 + \gamma \frac{K_{it}}{A_{it}}) \tag{3}$$

The left hand side of the equation is the log of the observed Tobin's q, defined as the ratio of market value to the replacement cost of the firm's physical assets. γ is the marginal or shadow value of the ratio of knowledge capital to physical assets. It captures the expectations of the investors over the effect of K on the discounted future profits of the firm. $\log q$ represents the intercept of the model, which is the average log of Tobin's q for the sample firms.

In order to test whether the market value of innovative assets is particularly affected we interact firm's R&D expenses with information ambiguity δ_{it} (see equation (4)). A negative coefficient of

[3] Note that in the absence of information ambiguity, i.e. $\delta_{it} = 0$, equation (2) becomes equation (1).

this interaction term would indicate that the otherwise positive effect of R&D on firms' market value is reduced if there is information ambiguity.

$$\log q_{it} = \log \frac{\tilde{V}_{it}}{A_{it}} = \delta_{it} + \log q + \log(1 + \gamma_1\, \delta_{it} \frac{R\&D_{it}}{A_{it}} + \gamma_2\, \delta_{it} \frac{PAT_{it}}{A_{it}}) \tag{4}$$

Equation (4) further tests whether (citation-weighted) patents mitigate the negative effect of information ambiguity δ_{it} on the market value of firm's assets. Such an effect would be indicated by a positive and significant coefficient for the interaction term $\gamma_2\, \delta_{it} \frac{PAT_{it}}{A_{it}}$.

4. Sample and variable definition

4.1. Sample

We assemble a rich dataset of annual firm level data from a variety of sources. First, firm-level accounting data for the years 1992 to 2006 come from Compustat. To this dataset, we merge data on analyst coverage from the Institutional Brokers Estimates System (I/B/E/S). Following prior research, we use the unadjusted summary dataset (Diether et al., 2002). This file includes various summary statistics at the firm level such as the number of analysts following a firm, as well as the mean, median, and standard deviation of the forecasts. Patent data comprising all U.S. utility patents granted between 1975 and 2006 and the citations that these patents receive from future patented inventions (we have citation data until 2010) come from the United States Patent and Trademark Office (USPTO). The patent dataset we use was originally compiled by Sampat (2011). We retrieve daily stock price data from the Centre of Research in Security Prices (CRSP). We include all stocks listed on the AMEX, NYSE, and NASDAQ. We also obtain daily Fama and French (1993) risk factors from Kenneth French's homepage.

Following prior literature (Hall et al., 2005), we restrict our study to firms in manufacturing industries (SIC 20-39). Even though there has been a shift towards services in recent years, manufacturing firms are still responsible for the bulk of R&D expenditures and patents. Further, limiting the study to manufacturing firms also ensures that a large share of the firms in our sample have material R&D expenditures. To ensure that the standard deviation of analysts' earnings forecast is a meaningful proxy for information ambiguity, we require all firms to be covered by at least two analysts in each calendar month in order to be included in the sample. We further exclude all firms for which we have less than two consecutive observations with non-missing data. Our final sample is an unbalanced panel with 3,670 firm-year observations corresponding to 382 firms in the manufacturing sector between 1992 and 2006. The panel structure is as follows: about 23% of the firms are observed for all fifteen years of the sample, about 15% are observed for ten to fourteen years, 35% are observed for six to nine years, and 27% of the firms are observed for four to five years.

4.2. Dependent variables

4.2.1. Information ambiguity

We define information ambiguity by analyst forecast dispersion which is calculated as the standard deviation of all outstanding analyst forecasts scaled by the mean consensus forecast for each calendar month. We aggregate forecast dispersion by computing the mean forecast dispersion over all month prior to a firm's earnings announcement.

Forecast dispersion is a widely accepted measure of information ambiguity, uncertainty, parameter risk, or estimation risk and is used in a large number of recent publications (Anderson et al., 2005, 2009; Doukas et al., 2006; Dittmar and Thakor, 2007; Erickson et al., 2012; Güntay and Hackbarth, 2010; Johnson, 2004; Kumar et al., 2008). Dispersion is a measure for disagreement among analysts and among market participants in general. When disagreement is high, market participants face the risk that stock prices will move more in line with the estimates of others (Dittmar and Thakor, 2007). If analysists produce very different and conflicting forecasts about the fundamentals of a firm, investors are likely to be unsure about the distribution of stock returns as they tend to condition their beliefs on the analysts' forecasts. This means that when dispersion among analysts' opinions regarding the future performance of a firm is high, ambiguity is high as well since investors cannot confidently narrow down the set of their beliefs to a single prior.[4]

4.2.2. Tobin's q

For testing the second and third hypothesis of this paper, we use Tobin's q – the ratio of firms' market value to the replacement costs of assets – as dependent variable. We compute the market value of assets as the sum of firm's market capitalization (shares outstanding multiplied by share price), long-term debt, and preferred stock. The replacement costs of assets are defined as the sum of property, plant, and equipment, inventories, and net short-term assets. We followed the definition by Konar and Cohen (2001). Tobin's q is a measure for the divergence of a firm's market value relative to the book value of the firm's assets.

4.3. Independent variables

4.3.1. R&D and patent stocks

R&D intensity is defined as the ratio of a firm's R&D stock and the book value of assets. We calculate firms' R&D stocks as a perpetual inventory of their past and contemporaneous R&D expenditures. We use a constant annual depreciation rate (δ) for R&D of 15% (Cockburn and Griliches, 1988; Griliches and Mairesse, 1984) and compute R&D stocks as:

$$RD_{it}^{stock} = (1-\delta) \times RD_{i,t-1}^{stock} + RD_{it}^{flow} \tag{5}$$

where the flow variable depicts firm's current year R&D expenditure as reported by Compustat.

[4] Note that the absence of information ambiguity does not imply that analysts agree if they separately assess the different risks associated with R&D based on public as well as private information.

We construct patent and citation stocks using the same perpetual inventory method and the same depreciation rate as for the R&D stock (Hall et al., 2005). The flow variables in the patent stock and citation stock measure corresponds to the number of a firm's annual patent applications later granted and the number of forward citations received by a firm's patents, respectively. Since we have at least 10 years of R&D, patent and citation data from the pre-sample period which we use for constructing the stock measures we do not correct for the initial value.

4.3.1. Firm size and reputation

Firm size and firm reputation are important variables in our study as they proxy a poor information environment. We measure firm size by the natural logarithm of the firms' employment (in thousands). It has been shown that larger firms have lower forecast dispersion (Thomas, 2002). We also obtain information on firms' Standard & Poor's credit ratings from the Compustat database. We define firms with a strong reputation in capital markets as firms with an investment grade (BBB or better) credit rating. We code firms with no credit rating and firms with a non-investment grade credit rating as low reputable firms leading to a binary variable following Diamond (1989).

4.3.2. Other control variables

In the first set of regressions, we include a number of additional variables that are likely to have an impact on information ambiguity. We control for share turnover by computing the average monthly trading volume of a firm's stock scaled by the average number of monthly shares outstanding. Turnover is a measure of a stock's liquidity. We expect firms with higher turnover to have a more transparent information environment. Hence, there should be a negative impact of turnover on forecast dispersion. We also control for industry growth at the three digit-SIC level using the ratio of industry sales (in thousand US$) in time t divided by industry sales in time $t\text{-}1$. Industry growth is a measure of the growth opportunities in a firm's environment. Finally, we create a dummy that takes the value 1 if a firm is headquartered in the U.S. and 0 otherwise. The returns of foreign firms are likely to be more difficult to forecast for analysts leading to higher forecast dispersion (Bae et al., 2008).

4.4. Descriptive statistics

Table 1 presents summary statistics, Table 2 bivariate correlations. The average R&D intensity equals 0.24 which is reflected in their Tobin's q which is well above unity.

--- Insert Table 1 here ---

--- Insert Table 2 here ---

As expected, the correlation between R&D intensity and the log of forecast dispersion is positive. Figure 1 plots the two variables against each other. It shows that forecast dispersion first declines at lower levels of R&D intensity and then monotonically increases as R&D intensity rises.

--- Insert Figure 1 here ---

5. Empirical results

5.1. R&D and information ambiguity

Table 3 presents results for the regressions testing hypothesis 1. We use the natural logarithm of forecast dispersion as dependent variable.[5] We present both pooled OLS regressions (where we simply pool all observations) and fixed effects regression (where we allow for firm-specific unobservable results).[6] Both the pooled OLS estimates and the fixed-effects estimates show a positive effect of R&D on forecast dispersion which is robust across the different specifications.

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[5] Note that the results do not change if we use forecast dispersion as dependent variable instead of the logarithm of forecast dispersion.

[6] We also estimated random effects regressions. Hausman tests rejected the null hypothesis of no systematic difference between the coefficients at the 1% level of statistical significance for all three specifications so that we present fixed effects regressions here.

An increase in R&D intensity by 1 increases forecast dispersion by 68%-117%. Since a 1-unit change of R&D intensity is unlikely to happen, we consider a change of R&D by one standard deviation (0.233). An increase in R&D by one standard deviation leads to an increase in forecast dispersion by 15.84%-27.26%.

Note that the finding that R&D increases forecast dispersion is not driven by the possibility that analysts screen innovative firms less often or less careful. On the contrary, Barth et al. (2001) document that firms with larger R&D expenses experience greater analyst coverage and that analysts' efforts for screening these firms are larger. Hence and in line with prior studies (Thomas, 2002; Gu and Wang, 2005), we interpret the fact that analysts show more disagreement when evaluating innovative firms as evidence for information ambiguity.

We expect that the positive effect of R&D over assets on forecast dispersion is stronger for smaller firms and firms that do not have an investment grade credit rating, as these types of firms tend to have particularly weak information environments. Models (2), (3), (5) and (6) show that this is actually the case because the effect of R&D on Forecast dispersion is mitigated by firm size and by having an investment grade. We conclude that R&D leads to a higher information ambiguity, especially among small firms and less reputed firms. These results support our hypotheses 1, 1a and 1b.

The control variables show the expected signs. Information ambiguity is higher for firms that have a foreign headquarter. We also find that growth opportunities at the industry level decrease information ambiguity. The effect of turnover is less clear. While we find a negative effect of turnover in the pooled cross-sectional models the sign changes if we take fixed effects into account. Although one might expect that patents reduce information ambiguity we do not find a significant effect of patents on forecast dispersion which is likely due to the skewness of the patent value distribution with most patents having no or little value (Harhoff et al., 1999). The patent citation stock has the expected negative sign in most specifications, but is insignificant.

--- Insert Table 3 here ---

5.2. Information ambiguity and the market value of R&D

As described in section 3.2 we estimate hedonic market value equations to assess the impact of information ambiguity on the market value of firms' innovative assets. We estimate equations (3) and (4) by non-linear least squares (NLLS) (e.g., Hall et al., 2005). We control for unobserved heterogeneity across firms by including the pre-sample mean of log Tobin's q from a five-year pre-sample period. Pre-sample mean estimators have the advantage that they do not require strict exogeneity (Blundell et al., 1995).[7]

Table 4 present the results. To benchmark our results with previous findings regarding the estimated coefficients for R&D, patent and citation stock, we present semi-elasticities for the knowledge stock variables along the estimates for the NLLS estimates. The semi-elasticities for R&D/Assets from our baseline model (1) are almost identical in size and magnitude to those shown in Hall et al. (2005: 30). Evaluated at the mean, an increase in R&D intensity by one percentage point (i.e., in the ratio of R&D/Assets) leads to an increase in market value by about 0.6%-0.7%. A unit change of citations over patent leads to a market value increase of about 1%. The estimated coefficient of the patent variable is not statistically significant per se. It only turns significant if weighted by citations (see model (4) of Table (4)). A unit change of citation weighted patent over R&D leads to a market value increase of about 0.5%.[8]

The coefficient of information ambiguity is negative and significant in all models indicating that information ambiguity is priced by the market and that investors require a compensation for information ambiguity. It follows from model (1) that the market value declines by 165% if forecast dispersion increases by one unit. A more realistic change of the forecast dispersion by 1 standard

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[7] Pre-sample means estimators have been used recently by Lach and Schankerman (2008) and Aghion et al. (2011).

[8] Our results hold if we use the flow of R&D rather than the stock.

deviation (0.08) decreases the market value by 13.2%. Model (2) shows the regressions including an interaction term between information ambiguity and knowledge assets. The estimated coefficient is negative and significant. These results support hypothesis 2 by showing that information ambiguity reduces the value of a firm's assets and particularly of its innovative assets.[9]

Model (3) includes an interaction between the patent variable and forecast dispersion. Both variables show a negative and significant sign. This means that a large patent portfolio itself does not provide a quality signal for the firms' R&D that the market considers as reliable. On the contrary, a large patent portfolio further reduces the market value in the presence of information ambiguity.

The last model (4) shows an interaction of citation-weighted patents with forecast dispersion. Here we find that high quality patents, in contrast to the finding in model (3) for the unweighted patent stock, provide information that is considered reliable by the market. The estimated coefficient shows a positive and significant effect indicating that the negative effect of information ambiguity on the market value of firm's assets is reduced by high quality patents.[10]

--- Insert Table 4 here ---

5.3. Graphical analysis of the results and a numerical example

Figure 2 shows the association between an increase in R&D and forecast dispersion that was described in section 5.1 graphically. The graph is based on model (4) of Table 3.

--- Insert Figure 2 here ---

[9] The results are not impacted by firms with a low analyst forecast coverage. Only 5% of the observations are followed by our required minimum of 2 analysts. We arrive at very similar results if we run the regressions for the subsample of firms that are followed by at least 5 analysts.

[10] Our results are robust to the use of a patent propensity measure and a citation-weighted patent propensity measure based on the patent activities of the past five years. The estimated coefficient signs are significant and point in the same direction. The coefficient size is as expected smaller.

Figure 3 illustrates the effects of forecast dispersion on the market value of innovative assets. The blue line depicts the effect of forecast dispersion at the means of all other variables along the R&D/assets distribution. The brown line shows the scenario without any forecast dispersion. The estimated market value is significantly higher along the entire R&D/assets distribution. The red line shows that a firm in the top 10% with regard to the citation weighted patent stock reaches the estimated market value of the situation without forecast dispersion for low R&D stocks over assets, i.e. firms with a small high quality R&D portfolio do not suffer market value reductions due to information ambiguity. For large R&D stocks over assets, however, a high quality patent stock does not suffice to outweigh the negative effect of information ambiguity on the estimated market value.

--- Insert Figure 3 here ---

Let us further illustrate the effects using a numerical example. If R&D/assets increase by one standard deviation (0.233) forecast dispersion increases by 15.84%-27.26% (based on the models presented in Table 3). An increase of R&D/assets by one standard deviation, from 0.60 to 0.83, for instance, then increases the logarithm of the market value by 0.14, i.e. an increase of the market value by 0.43, for firms that are not exposed to forecast dispersion; while the logarithm of the market value increases by 0.06, i.e. an increase of the market value by 0.24, for firms facing the average amount of forecast dispersion in our sample. This difference is substantial.

5.4. Information ambiguity and idiosyncratic risk

There is some concern that it is difficult to distinguish information ambiguity from idiosyncratic risk (Zhang, 2006). Idiosyncratic risk as measured by the residual from a 3-factor Fama-French model (see the Appendix for details on the calculation of this measure and an illustration of the development of both measures over time) is not highly correlated with our measure for information ambiguity (see Figure 4 in the Appendix) giving raise to the assumption that both measures account for different concepts. Table 5 shows that our results hold, when the measure for idiosyncratic risk is included in our regression models.

--- Insert Table 5 here ---

5.5. Robustness check: Instrumental variable analysis

Another concern is endogeneity of forecast dispersion in the market value model as both forecast dispersion and the market value are determined by R&D. Therefore, we use a novel instrumental variables (IV) approach suggested by Lewbel (2012) which allows identification based on higher moments without the need for outside instruments. Lewbel (2012) shows that if no traditional instrumental variables are available parameters of a triangular or fully recursive system can still be identified if errors are heteroskedastic. Following Lewbel (2012) we exploit heteroscedasticity in the first stage residuals of a two stage least squares regression and construct a vector of instruments $(X-\bar{X})\hat{e}$, where X corresponds to the exogenous variables in the model and $\hat{e}$ to the first-stage residuals. We employ the IV estimation for a linear approximation of the market value equation.

Table 6 shows our results from the non-linear least squares estimation in the first column. The second column shows a linear approximation of the market value equation which we estimated by OLS. The estimated coefficients are remarkably similar, in particular for forecast dispersion, our variable of main interest. This makes us confident to proceed with the linear approximation. The third column presents the IV estimation results. Here we see that the estimated effect of forecast dispersion on Tobin's Q remains statistically significant if endogeneity is taken into account. The magnitude of the coefficient decreases only slightly.

--- Insert Table 6 here ---

5.6. Robustness check: Controlling for firms' innovativeness

One might be concerned that our results are affected by the fact that more innovative firms file patents that are more novel. This effect has been captured so far by the firm specific unobservable effects. Now, we control for the innovativeness of the firm by proxying it as the residual from a simple fixed effects poisson patent production function with citation-weighted patents as dependent variable and the R&D stock and year dummies as regressors. Due to the skewness of the residual's distribution, we normalized it by the R&D stock of the firm and used it as an additional regressor. Table 7 shows that the results previously presented in Table 4 are not affected by the omission of a control for the firms' innovativeness.

--- Insert Table 7 here ---

6. Conclusions and Implications

Though R&D is an important driver of firms' market value (Griliches, 1981; Hall et al., 2005), there is consistent evidence that innovative assets are undervalued by the market (e.g. Eberhart et al., 2004). We argue that this can be partly explained by the information ambiguity that arises due to the specific features of R&D, which include a long term character and uncertain outcomes (Holmstrom, 1989) as well as intangibility and appropriation problems due to externalities (Arrow, 1962).

Based on an empirical analysis for U.S. manufacturing firms, we show that R&D increases information ambiguity about the value of firms' assets. We find this effect to be particularly strong for firms in weak information environments. We further show that the market value of firms is shifted downwards indicating that investors require a compensation for an investment in firms surrounded by information ambiguity. Our results uncover that in particular the market value of innovative assets is lower in the presence of information ambiguity. Lastly, we show that high quality patents counteract the negative effects of information ambiguity.

Our findings contribute to the literature on R&D and uncertainty. We illustrate the importance of information ambiguity as a value factor for R&D. Prior studies have mainly focused on risk - market risk and technological risk - in the R&D - market value relationship (e.g., Bloom and Van Reenen, 2002; Oriani and Sobrero, 2008, Czarnitzki and Toole, 2011). By showing that information ambiguity reduces the valuation of innovative assets - on top of the risk reductions - and that high quality patents mitigate this effect we contribute to a small, but developing literature on the effects of information ambiguity for the evaluation of innovative assets (Thomas, 2002; Eberhart et al., 2004; Gu and Wang, 2005, Lev et al., 2005).

Our findings have important implications. First, by inducing an ambiguity compensation for investors, information ambiguity exacerbates financial constraints and difficulties to finance innovative projects externally. The wedge between the costs of internal and external financing increases so that internal funds become more important for the financing of R&D than for ordinary investment (e.g. Hall, 1992; Himmelberg and Petersen, 1994; Czarnitzki and Hottenrott, 2011). The finding that information ambiguity is especially strong for small firms and those with little reputation speaks to the well-established fact that financial constraints are particularly high for small and young firms (Himmelberg and Petersen, 1994). The finding shows that especially small and young firms should take initiative to convince investors of their trustworthiness. Having good financial figures helps. In addition, the management of young and small firms can take measures to signal their quality such as patents, a network of investors and firms with a strong reputation and a well design disclosure policy towards its investors.

Second, it is important to understand that the managerial means to counteract information ambiguity are different from those against risk. To reduce technological risk innovation managers can engage in less radical and rather incremental innovation project. If managers aim at reducing market risk they can invest in market research and involve customers early on in the new product development process. In the presence of information ambiguity managers face a difficult decision.

Firms could employ disclosure mechanisms disseminating information about their ongoing R&D projects to reduce information ambiguity (e.g. Lev, 2001; Jones, 2007). Disclosure is a possible means to counteract the negative implications of information ambiguity where investors face uncertainty about the probabilities over payoffs. Disclosure would however come at the cost of sharing valuable information with potential competitors and foregoing a competitive advantage, which in turn would lower the value of firms' innovative assets. Note that disclosure would not be an effective means against risk where there is uncertainty over payoffs where corporate insiders may not have superior information.

We suggest a way out of this dilemma. The finding that high quality patents mitigate the negative effect of information ambiguity encourages innovation management to pay careful attention to intellectual property management. Innovation managers may want to question the patenting of marginal inventions and focus on a few high quality patents if their aim is to limit information ambiguity surrounding their innovation activities.

A policy implication that arises from our results is that especially innovative small and young firms, those in a poor information environment with needs to access external finance, may be supported by advice on intellectual property management.

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Appendix

We computed idiosyncratic volatility from daily stock returns and two Fama and French (1993) risk factors. The advantage of using high-frequency stock market data for measuring risk is that stock prices, in principle, include all factors in a firm's environment that investors perceive to be important (Gilchrist et al., 2010). Similar to Ang et al. (2009) and Fu (2009: 26), we estimate firm-specific risk from the following model:

$$(r_{it_d} - r^f_{t_d}) = \alpha_i + \beta_i^M (r^M_{t_d} - r^f_{t_d}) + \beta_i^{SMB} SMB_{t_d} + \beta_i^{HML} HML_{t_d} + u_{it_d}, \tag{6}$$

where i indexes firms, t_d indexes trading days in year t. In equation (6), r_i denotes the firm's daily stock return, r^f is the one-month treasury bill rate (i.e., the risk-free rate), r^M is the value-weighted return on the market as a whole, SMB is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, and HML is the difference between the return of a portfolio of high book-to-market stocks and the return on the portfolio of low book-to-market stocks. Idiosyncratic volatility is defined as the standard deviation of the residual obtained from (6). Measuring ambiguity by stock market data is widely accepted in the economics literature. Recent examples are Baum et al. (2007), Bloom and Van Reenen (2002), and Bloom et al. (2007).

Hussinger and Pacher (2015) provide evidence suggesting that idiosyncratic risk and analyst forecast dispersion reinforce each other. A further inspection of the developments of forecast dispersion and idiosyncratic volatility suggests that the two variables are affected by different forces. Idiosyncratic volatility over time has been investigated recently by Campbell et al. (2001) and Brandt et al. (2010). Brandt et al. (2010: 868) show that idiosyncratic volatility has increased steadily since the 1960s but especially during the second half of the 1990s. Volatility peaked in 2000 and decreased sharply in the years thereafter. Idiosyncratic volatility follows a very similar pattern in our data. Figure 4 shows that idiosyncratic volatility is roughly stable between 1992 and 1996, increases sharply during 1997 to 2000, and declines in the years after the burst of the technology bubble. In contrast, it seems that forecast dispersion declined in the first half of the 1990s. There is a relatively strong increase in forecast dispersion in early 2001 and 2002, probably reflecting the burst of the technology bubble and the subsequent 2001 recession. Overall, Figure 4 suggests that analyst forecast dispersion captures a different effect than the standard measure for idiosyncratic volatility.

--- Insert Figure 4 here ---

We further repeat our main regression with idiosyncratic volatility included as an additional regressor (see Table 5). Idiosyncratic volatility exhibits a significant negative effect on the market value, but the results for information ambiguity and innovative assets do not change.

TABLES AND FIGURES

Table 1: Summary statistics

Variable	Mean	S.D.	Min.	Median	Max.
Forecast dispersion	0.058	0.080	0.002	0.032	0.868
Log (Forecast dispersion)	-3.381	0.990	-6.328	-3.436	-0.141
Tobin's q	2.480	1.780	0.491	1.909	19.413
Presample mean of Tobin's q	2.402	2.07	0.551	1.788	23.209
Log (Tobin's q)	0.744	0.533	-0.712	0.646	2.966
R&D stock/Assets	0.241	0.233	0.000	0.166	1.985
Patent stock/R&D stock	3.670	23.304	0.000	0.312	495.647
Citation stock/Patent stock	14.330	9.684	0.000	11.929	65.791
Log (Employment)	2.053	1.524	-3.297	2.041	6.186
Inv. grade credit rating (INV)	0.451	0.498	0.000	0.000	1.000
Log (Turnover)	6.563	0.963	1.075	6.582	9.678
Industry growth	0.075	0.121	-0.619	0.071	1.578
Foreign firm dummy	0.050	0.217	0.000	0.000	1.000

Notes: N = 3,670 firm-year observations. Year and industry dummies are omitted for space reasons.

Table 2: Correlation matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. Log (Forecast dispersion)	1.000								
2. Log (Tobin's q)	-0.351***	1.000							
3. R&D stock/Assets	0.086***	0.270***	1.000						
4. Patent stock/R&D stock	-0.064***	0.096***	-0.147***	1.000					
5. Citation stock/Patent stock	0.014	0.236***	0.257***	-0.016	1.000				
6. Log (Employment)	-0.166***	-0.027	-0.111***	0.020	-0.153***	1.000			
7. Inv. grade credit rating (INV)	-0.178***	0.084***	-0.085***	-0.010	-0.154***	0.668***	1.000		
8. Log (Turnover)	0.028	0.066***	0.184***	-0.063***	0.193***	-0.169***	-0.085***	1.000	
9. Industry growth	-0.038*	0.083***	0.079***	-0.043**	0.086***	-0.025	-0.050**	0.069***	1.000
10. Foreign firm dummy	0.145***	-0.034*	-0.005	-0.035*	-0.137***	0.160***	0.075***	-0.362***	0.020

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). N = 3,670 firm-year observations. Year and industry dummies omitted for space reasons.

Table 3: Determinants of information ambiguity

Dependent variable: Log (Forecast dispersion)

Variable	(1) Pooled	(2) Pooled	(3) Pooled	(4) FE	(5) FE	(6) FE
R&D stock/Assets	0.680***	0.856***	0.837***	0.942***	1.138***	1.172***
	(0.082)	(0.116)	(0.095)	(0.155)	(0.190)	(0.168)
Patent stock/R&D stock	0.000	0.000	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Citation stock/Patent stock	-0.001	-0.007	-0.002	0.000	0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Log (Employment)	-0.129***	-0.089	-0.118***	-0.181***	-0.145***	-0.175***
	(0.016)	(0.023)	(0.017)	(0.043)	(0.048)	(0.043)
Log (Turnover)	0.115***	0.110***	0.108***	-0.091***	-0.090***	-0.088***
	(0.022)	(0.022)	(0.022)	(0.033)	(0.033)	(0.033)
Industry growth	-0.435***	-0.441***	-0.451***	-0.406***	-0.415***	-0.426***
	(0.126)	(0.126)	(0.125)	(0.109)	(0.109)	(0.109)
Inv. grade credit rating	-0.114**	-0.122***	0.015	-0.102*	-0.103*	0.095
	(0.046)	(0.046)	(0.054)	(0.059)	(0.059)	(0.081)
Foreign firm	0.924***	0.897***	0.881***			
	(0.085)	(0.086)	(0.086)			
R&D stock/Assets * Log (Employment)		-0.119***			-0.147*	
		(0.049)			(0.081)	
R&D stock/Assets * INV			-0.568***			-0.741***
			(0.148)			(0.209)
Constant	-3.105***	-3.203***	-3.162***	-2.232***	-2.279***	-2.307***
	(0.210)	(0.210)	(0.205)	(0.228)	(0.230)	(0.229)
F test on joined significance						
Year dummies	12.75***	12.90***	13.03***	9.51***	9.54***	9.68***
Industry dummies	21.42***	20.24***	20.42***			
# of observations	3,651	3,651	3,651	3,651	3,651	3,651
R-Squared	0.337	0.339	0.340			
F-stat				17.52***	16.89***	17.37***

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). The pooled OLS models include a full set of 14 year dummies and industry dummies at the two-digit SIC level. The FR regressions contain a full set of year dummies. Heteroscedasticity robust standard errors clustered at the firm-level are in parentheses. Year and industry dummies omitted for space reasons.

Table 4: Ambiguity and the market value of R&D

Dependent variable: Log (Tobin's q)

	(1)	(2)	(3)	(4)
Variable	NLLS	NLLS	NLLS	NLLS
R&D stock/Assets	0.732***	0.931***	0.929***	0.810***
	(0.182)	(0.225)	(0.225)	(0.190)
Patent stock/R&D stock	0.002	0.002	0.005	
	(0.002)	(0.002)	(0.004)	
Citation stock/Patent stock	0.013***	0.013***	0.013***	
	(0.004)	(0.005)	(0.005)	
Citation weighted patent stock/R&D stock				0.006***
				(0.002)
Forecast dispersion	-1.649***	-1.220***	-1.140***	-1.283***
	(0.151)	(0.193)	(0.192)	(0.202)
R&D stock/Assets * Forecast dispersion		-1.298**	-1.370***	-1.394***
		(0.523)	(0.525)	(0.514)
Patent stock/R&D stock * Forecast dispersion			-0.074**	
			(0.037)	
Citation weighted patent stock/R&D stock * Forecast dispersion				0.017**
				(0.008)
Presample-mean of Tobin's q	0.239***	0.242***	0.242***	0.278***
	(0.032)	(0.032)	(0.032)	(0.032)
Constant	0.761***	0.732***	0.727***	0.815***
	(0.091)	(0.093)	(0.091)	(0.084)
Semi-elasticities (dy/dx)[a]				
R&D stock/Assets	0.550***	0.676***	0.673***	0.683***
	(0.123)	(0.143)	(0.143)	(0.139)
Patent stock/R&D stock	0.001	0.001	0.004	
	(0.001)	(0.001)	(0.003)	
Citation stock/Patent stock	0.010***	0.010***	0.009***	
	(0.003)	(0.003)	(0.003)	
Citation weighted patent stock/R&D stock				0.005***
				(0.002)
Chi2 test on joined significance				
Year dummies	0.25	0.37	0.26	0.05
Industry dummies	33.94***	35.37***	35.36***	25.18***
# of observations	3,651	3,651	3,651	3,661
R-Squared	0.360	0.364	0.366	0.361

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). The models include a full set of year dummies and industry dummies at the two digit-SIC level. Standard errors for models are robust to arbitrary heteroscedasticity and are clustered at the firm-level. Standard errors are computed using the Delta-method.

Table 5: Ambiguity and the market value of R&D – including idiosyncratic volatility

Dependent variable: Log (Tobin's q)

Variable	(5) NLLS	(6) NLLS	(7) NLLS	(8) NLLS
R&D stock/Assets	0.752***	0.943***	0.941***	0.816***
	(0.184)	(0.225)	(0.225)	(0.189)
Patent stock/R&D stock	0.002	0.002	0.005	
	(0.002)	(0.002)	(0.004)	
Citation stock/Patent stock	0.014***	0.014***	0.014***	
	(0.005)	(0.005)	(0.005)	
Citation weighted patent stock/R&D stock				0.006***
				(0.002)
Forecast dispersion	-1.492***	-1.082***	-1.004***	-1.190***
	(0.147)	(0.186)	(0.185)	(0.195)
R&D stock/Assets * Forecast dispersion		-1.249**	-1.320**	-1.356***
		(0.509)	(0.512)	(0.508)
Patent stock/R&D stock * Forecast dispersion			-0.073**	
			(0.037)	
Citation weighted patent stock/R&D stock * Forecast Dispersion				0.015**
				(0.007)
Idiosyncratic volatility	-0.057***	-0.056***	-0.055***	-0.038**
	(0.018)	(0.018)	(0.018)	(0.018)
Presample-mean of Tobin's q	0.257***	0.259***	0.260***	0.292***
	(0.031)	(0.031)	(0.031)	(0.031)
Constant	0.817***	0.787***	0.782***	0.860***
	(0.089)	(0.091)	(0.090)	(0.085)
Semi-elasticities (dy/dx)[a]				
R&D stock/Assets	0.550***	0.678***	0.675***	0.688***
	(0.123)	(0.143)	(0.142)	(0.139)
Patent stock/R&D stock	0.001	0.001	0.004	
	(0.001)	(0.001)	(0.003)	
Citation stock/Patent stock	0.010***	0.010***	0.009***	
	(0.003)	(0.003)	(0.003)	
Citation weighted patent stock/R&D stock				0.005***
				(0.002)
# of observations	3,651	3,651	3,651	3,651
R-Squared	0.366	0.369	0.371	0.364

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). The models include a full set of year dummies and industry dummies at the two digit-SIC level. Standard errors for models are robust to arbitrary heteroscedasticity and are clustered at the firm-level. Standard errors are computed using the Delta-method.

Table 6: Endogeneity of forecast dispersion

Dependent variable: Log (Tobin's q)

Variable	(1) NLLS	(2) OLS	(3) Lewbel IV
R&D stock/Assets	0.732***	0.426***	0.407***
	(0.182)	(0.104)	(0.105)
Patent stock/R&D stock	0.002	0.001	0.001**
	(0.002)	(0.001)	(0.001)
Citation stock/Patent stock	0.013***	0.008***	0.008***
	(0.004)	(0.003)	(0.003)
Forecast dispersion	-1.649***	-1.655***	-1.252***
	(0.151)	(0.154)	(0.194)
Presample-mean of Tobin's q	0.239***	0.252***	0.253***
	(0.032)	(0.033)	(0.033)
Constant	0.761***	0.809***	0.785***
	(0.091)	(0.088)	(0.092)
# of observations	3,651	3,651	3,651
R-Squared	0.360	0.354	0.351
Kleibergen-Paap LM statistic			123.691
Cragg-Donal Wald F statistic			76.734

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). The models include a full set of year dummies and industry dummies at the two digit-SIC level. Standard errors for model 1 are robust to arbitrary heteroscedasticity and are clustered at the firm level. Standard errors are computed using the Delta-method. Standard errors for models 2 and 3 are robust and clustered at the firm level.

Table 7: Ambiguity and the market value of R&D – controlling for innovativeness

Dependent variable: Log (Tobin's q)

	(1)	(2)	(3)	(4)
Variable	NLLS	NLLS	NLLS	NLLS
R&D stock/Assets	0.721***	0.731***	0.725***	0.828***
	(0.182)	(0.226)	(0.226)	(0.190)
Patent stock/R&D stock	0.004*	0.004*	0.008*	
	(0.002)	(0.002)	(0.004)	
Citation stock/Patent stock	0.013***	0.013***	0.013***	
	(0.005)	(0.005)	(0.005)	
Citation weighted patent stock/R&D stock				0.006**
				(0.002)
Forecast dispersion	-1.624***	-1.177***	-1.103***	-1.277***
	(0.150)	(0.191)	(0.191)	(0.199)
Innovativeness	0.002***	0.002***	0.002***	0.001*
	(0.001)	(0.001)	(0.001)	(0.000)
R&D stock/Assets * Forecast dispersion		-1.350***	-1.419***	-1.277***
		(0.521)	(0.524)	(0.512)
Patent stock/R&D stock * Forecast dispersion			-0.069	
			(0.030)	
Citation weighted patent stock/R&D stock * Forecast Dispersion				0.016**
				(0.008)
Presample-mean of Tobin's q	0.235***	0.237***	0.238***	0.277***
	(0.032)	(0.032)	(0.032)	(0.032)
Constant	0.762***	0.731***	0.725***	0.828***
	(0.089)	(0.091)	(0.090)	(0.084)
# of observations	3,651	3,651	3,651	3,631
R-Squared	0.366	0.370	0.371	0.363

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). The models include a full set of year dummies and industry dummies at the two digit-SIC level. Standard errors for models are robust to arbitrary heteroscedasticity and are clustered at the firm-level. Standard errors are computed using the Delta-method.

Figure 1: R&D Intensity vs. Log (Forecast dispersion)

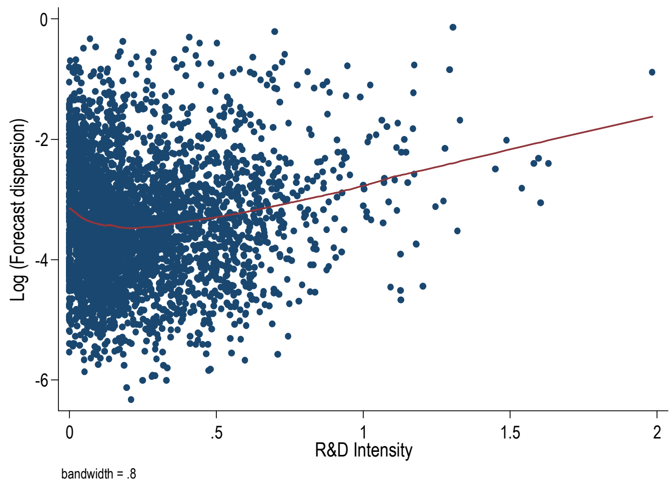

Figure 2: Effect of R&D on Forecast Dispersion

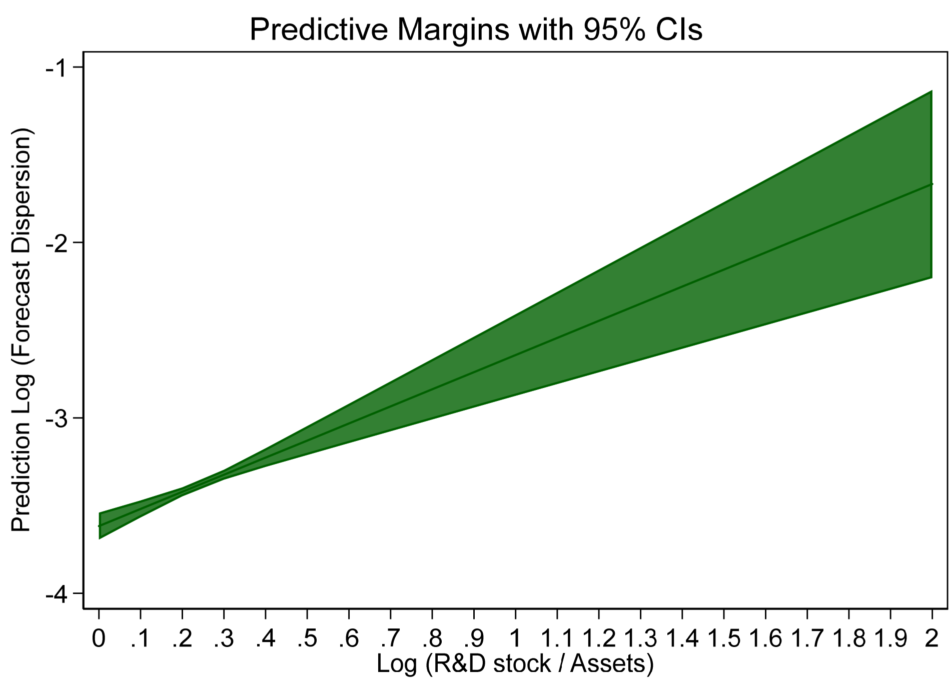

Figure 3: Effect of Forecast Dispersion on the Market Value of R&D

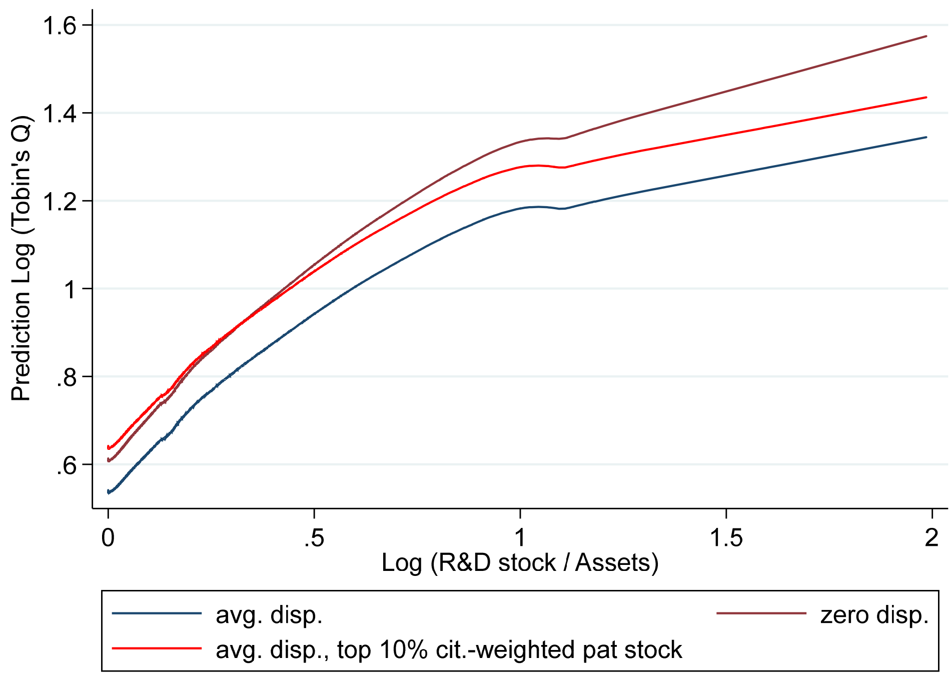

Figure 4: Idiosyncratic volatility and forecast dispersion from 1992 to 2006