Innovation under Risk and Ambiguity

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Abstract

We explore the implications of ambiguity (Knightian uncertainty) and risk for innovation decisions through the lens of real options. We find that innovation investments are significantly affected by both risk and ambiguity. In particular, we document a negative relation between ambiguity and innovation input (R&D investment), as well as intermediate innovation output (patents and citations). We also find that small firms "care" more about ambiguity, whereas risk is more significant for innovation decisions by large firms. These results show that ambiguity and risk capture separate dimensions of uncertainty, which affect investment decisions in general, and innovation in particular, in different ways.

Keywords: Ambiguity measurement, Ambiguity aversion, Risk aversion, Innovation, Patents

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1 Introduction

A large and growing body of literature investigates the determinants of innovation; such determinants include industry competition (Aghion et al., 2005), institutional ownership (Aghion et al., 2013) and organizational structure (Lerner et al., 2011, Seru, 2014, Bernstein, 2015). Special attention has been given to uncertainty as a driver of innovative activity. Bernstein et al. (2017) suggest that economic risk (negative housing shocks) reduces employees' interest in risky and exploratory projects. Krieger et al. (2017) investigate the tradeoff between conservative and riskier investments in drug development. Our paper contributes to this chain of ideas, by making the distinction between two aspects of uncertainty: risk and ambiguity (Knightian uncertainty). Risk is a condition where the realized outcome is a priori unknown, but the odds of all possible outcomes are perfectly known. Ambiguity is a condition where not only is the realized outcome a priori unknown, but also the odds of possible outcomes are unknown or not uniquely assigned.[1] Clearly, firms face both types of uncertainty. Our paper aims to empirically investigate which type of uncertainty is more salient for innovating firms.

Most work to date has focused on risk—the uncertainty of outcomes—measured mainly by the variance of outcomes. Risk, however, assumes a unique quantifiable distribution of future prospects. In reality, it may be very difficult (and, perhaps, impossible) to predict a distribution of future outcomes for a new innovative product such as a new drug (Krieger et al., 2017). Therefore, the concept of ambiguity—the uncertainty of probabilities—seem a natural lens through which managers may view future prospects. Firms may make different decisions about innovative investments in the face of ambiguity, as risk and ambiguity bear different implications for evaluating investment opportunities.

We follow Schwartz (2004) and consider patent and R&D decisions as real options. However, while in Schwartz (2004) the values of these real options are subject to risk only, in a different strand of literature, Izhakian and Yermack (2017) and Augustin and Izhakian (2016) show that option values are significantly affected by ambiguity. Our testable hypotheses combine the insights from these two approaches, and are supported by a one-period stylized model of an optimal investment

[1] Knight (1921) defines the concept of (Knightian) uncertainty, distinct from risk, as conditions under which the set of events that may occur is a priori unknown, and the odds of these events are either not unique or are unknown.

decision through the lens of real options in the presence of risk and ambiguity (presented in the Appendix).

The model shows, in a simple framework, that risk and ambiguity have very different effects on investments decisions. Any investor, and in particular risk-averse or even risk-neutral investors, is motivated to invest more in a real option as risk increases. Any ambiguity-averse decision maker is motivated to invest less in a real option as ambiguity increases. Thus, while risk has a positive effect on investment decisions, the effect of increased ambiguity is negative. The intuition is that higher risk is associated with a higher value of a real option, which encourages investment. In contrast, since higher ambiguity leads decision makers to overweight the likelihood of bad outcomes and underweight the likelihood of good outcomes (e.g., Izhakian and Yermack, 2017), higher ambiguity reduces the perceived attractiveness of investment opportunities (i.e., a lower perceived expected return).

Several behavioral studies support these ideas in an experimental framework. These papers show that, while making decisions, individuals prefer alternatives involving clear probabilities (risk, the *known unknowns*) over alternatives involving vague probabilities (ambiguity, the *unknown unknowns*), even if normative theory (Savage, 1954) implies indifference. This phenomenon of ambiguity aversion (Ellsberg, 1961) has been shown to be economically relevant and to persist in experimental market settings and among business owners and managers.[2]

We test our hypotheses on innovating firms. While the theory encompasses any investment, in practice we expect our ideas to have more bite in cases where there is significant uncertainty about the future prospects of the investment in question, rather than say, in renovations or expansions of an existing product lines. For example, it would be difficult to view an investment in refurbishing an office building (which would appear under CAPEX in firms' accounting statements) as a real option. However, investment in a new lab, which may create an option to commercially license a new drug (and would appear under R&D), creates a real option, and thus is closer to our theoretical setting. This distinction is consistent with the accounting treatment of R&D as expenses and the requirement to depreciate CAPEX investments. Therefore, our main regression tests use R&D and patenting activity as dependent variables.

Empirically, we find a consistent negative effect of ambiguity on innovation input (R&D in-

[2]See, for example, Viscusi and Chesson (1999), Maffioletti and Michele (2005), Wakker et al. (2007), Mangelsdorff and Weber (1994), Abdellaoui et al. (2005), and Du and Budescu (2005).

vestment), as well as on innovation and intermediate output (patents and citations). In Poisson regressions, the predicted number of patents three years ahead decreases by 2.546 when moving from the 10th to the 90th percentile of ambiguity. This effect is both statistically and economically significant, given that the median firm in the sample of patenting firms files 3 patent applications per year. We find similar effects of ambiguity on the number of citations received by these patents. The same holds when estimating a Negative Binomial model instead of Poisson.

Further, we identify that the effect of ambiguity on innovation is driven by small and young firms. Firms that are further along their life cycle seem to be less affected by ambiguity, rather their innovative activity is significantly affected by risk. We observe that these firms increase their R&D and patenting activity as risk increases. Reasonably, young firms, with no earning or product success history, are more concerned with the effects of ambiguity, whereas large firms, with a proven track record, view risk as the most relevant dimension of uncertainty.

The main empirical tests use OLS as well as count regression models, which are standard in the patent literature. These tests include the common controls and adjustments for excess zeros when needed. We conduct numerous robustness tests, where firms are classified according to different criteria, including size, age, exchange listings and financial constraints. The results remain qualitatively consistent.

Empirically, our findings are in line with Herron and Izhakian (2017), who find that firm-level risk decreases and delays dividend payouts and share repurchases, while firm-level ambiguity increases and accelerates dividend payouts and share repurchases. Other prior literature regarding ambiguity focuses primarily on the theoretical aspects of ambiguity aversion.[3]

It seems almost self-evident that uncertainty of all types affects investment decisions that are inherent to innovation. To the best of our knowledge, there has not yet been a paper that integrates the effect of risk and ambiguity on innovative firms behavior. This paper seeks to fill that gap.

The remainder of this paper is organized as follows. Section 2 presents a discussion of ambiguity and develops the hypotheses. Section 3 describes the sample selection and data construction, including the estimates of the ambiguity and risk variables that are central to our investigation. Sections 4 presents the empirical methodology, and 5 reports the results. Section 6 concludes.

[3]Special attention has been given to the implications of ambiguity for the equity premium; see, for example, Cao et al. (2005), Nau (2006), Epstein and Schneider (2008) and Izhakian and Benninga (2011). For recent surveys about different implications of ambiguity for asset pricing, see Epstein and Schneider (2010) and Guidolin and Rinaldi (2013).

2 Ambiguity

2.1 Decision theoretic framework

Ambiguity, or Knightian uncertainty, provides the basis for a rich literature in decision theory. These models struggle to provide outcome-independent ambiguity preferences accompanied by complete separations between risk and ambiguity and between beliefs and tastes that allow ambiguity to be measured independently of risk.[4] Therefore, it is challenging to use previous models of decision making to investigate the implications of ambiguity empirically. For this reason, we use Izhakian's (2017) expected utility with uncertain probabilities (EUUP) framework to distinguish the concepts of risk and ambiguity. In EUUP, preferences for ambiguity are outcome-independent, thereby this framework provides a complete separation between risk and ambiguity and between beliefs and tastes. Thus, in our empirical investigation, we use a measure of ambiguity that is independent of attitudes toward ambiguity and risk.

Under EUUP, individuals act as if they solve a two-stage decision-making problem. In the first stage, the decision maker forms a representation of perceived probabilities for each relevant event based on the ambiguity associated with the probability of the event and her tastes concerning (attitudes toward) this ambiguity. In the second stage, the decision maker considers the expected utility associated with a set of possible outcomes, where the expectation is taken with respect to her perceived probabilities. The main idea of EUUP is that in the presence of ambiguity (i.e., when probabilities are uncertain), preferences concerning ambiguity are applied solely to probabilities (outcome independent) such that aversion to ambiguity is defined as aversion to mean-preserving spreads in probabilities. As such, the Rothschild and Stiglitz (1970) approach, typically applied to outcomes when examining risk, is applied to probabilities when examining ambiguity, independent of risk. In this framework, an ambiguity-averse individual overweights the probabilities of bad outcomes and underweights the probabilities of good outcomes. In particular, the higher the ambiguity, the lower the perceived probabilities of good outcomes and the higher the perceived probabilities of bad outcomes. As a result, when ambiguity rises, the perceived expected utility

[4] For example, in the min-max expected utility theory (Gilboa and Schmeidler, 1989), the set of priors captures both beliefs and tastes regarding ambiguity. As well, the capacities (sub-additive probabilities) used in the Choquet expected utility theory (Schmeidler, 1989) and the cumulative prospect theory (Tversky and Kahneman, 1992) reflect both beliefs and tastes over ambiguity.

computed with perceived probabilities falls. We formally describe this decision theory framework in the Appendix.

Based on EUUP, Izhakian (2016) shows that the degree of ambiguity can be measured by the volatility of probabilities—just as the degree of risk has been measured by the volatility of outcomes.[5] Unlike other proposed measures of ambiguity, which are outcome-dependent and risk-dependent and consider only the variance of a single moment of the outcome distribution (i.e., the variance of the mean or the variance of the variance), the Izhakian (2016) measure is attitude-independent, outcome-independent, risk-independent and conceptually accounts for the variance of all moments of the outcome distribution. Therefore, the EUUP measure of ambiguity can be employed in empirical studies using equity market data (e.g., Brenner and Izhakian, 2017, Izhakian and Yermack, 2017).

2.2 Real options view

Innovation investments can be viewed as real options. Consider, for example, a decision to invest in a new drug or a new technology. The firm will make an initial investment in R&D or a patent, only if the value of the option created is positive, given the "exercise price" (i.e., the eventual outlay). However, the firm can also decide to shelve the development at a later stage (in real life, the drug development process can be viewed as a sequence of real options).

It is well known that the value of a (real) option increases in risk. In contrast, this will not be the case for the effect of ambiguity. Through the lens of EUUP, higher ambiguity leads firms and decision makers to overweight the likelihoods of bad outcomes and underweight the likelihoods of good outcomes. When valuing a real option using EUUP (or some other models of ambiguity), higher ambiguity reduces the perceived value of the option. The intuition is that the higher the ambiguity, the lower is the perceived probability of a positive payoff, which the decision maker uses to forms the expected value of the (real) option. Assuming no conflicts of interest, managers act to maximize the (expected) value of the firm. Thus, within this framework, higher risk encourages investments. While, in contrast, higher ambiguity suppresses investments. Next, we provide a

[5]Other models do not permit derivation of an ambiguity measure since either ambiguity is not distinguished from aversion to ambiguity (e.g., Gilboa and Schmeidler, 1989, Schmeidler, 1989) or aversion to ambiguity is defined as aversion to mean-preserving spreads in certainty equivalent utilities, which are subject to both risk and aversion to risk (e.g., Chew and Sagi, 2008).

simple illustrative numerical example that shows how our intuition works. A theoretical model is provided in the Appendix.

2.3 Binomial example

Consider a one-period binomial real option for a project which requires an eventual investment of \$100.[6] Suppose that after one period, the payout of the project may either be $H = \$120$ or $L = \$80$, high and low respectively. The firm can buy the option to invest and then decide whether to put in the required amount when the state of the world materializes. In the case of high payoff, i.e., $H > 100$, the option pays the difference between the investment I (which is \$100) and the project's value, i.e., $H - I = \$120 - \$100$. If the low case materializes, the firm will not pursue the investment. For simplicity, assume that the risk-free rate is zero.

When the probabilities of both the bad and the good outcomes are exactly 50% (no ambiguity is present), the variance of the probabilities is 0. Therefore, the value of the option (in terms of expected utility) is $C = 0.5 \times (120 - 100) = 10$. If the risk of the project increases, such that the outcomes in the good and bad states are 130 or 70, respectively, then the value of the option increases to $C = 0.5 \times (130 - 100) = 15$. Thus, an increase in risk is associated with a higher value of the option. This is naturally less pronounced for risk-averse decision makers.[7]

To examine the impact of ambiguity, assume instead that the probabilities of the future outcomes are ambiguous. Good and bad outcomes occur with probability distributions $(0.4, 0.6)$ or $(0.6, 0.4)$. The decision maker, who does not have any information regarding the precision of these probability estimates, acts as if he assigns an equal weight to each state probability. In this case, the expected probability of the good state is $\mathrm{E}[\varphi(H)] = 0.5 \times 0.4 + 0.5 \times 0.6 = 0.5$ and its variance is $\mathrm{Var}[\varphi(H)] = 0.5 \times (0.4 - 0.5)^2 + 0.5 \times (0.6 - 0.5)^2 = 0.01$. The same values apply for the bad state. This implies that the degree of ambiguity is $\mho^2 = 0.5 \times 0.01 + 0.5 \times 0.01 = 0.01$.

In EUUP, an ambiguity-averse decision maker uses the certainty equivalent probabilities to asses her expected utility. A certainty equivalent probability is the unique certain probability value that the decision maker is willing to accept in exchange for the uncertain probability of a given

[6] The EUUP framework allows different combinations of risk attitude and ambiguity attitude. Typically, we expect decision makers to be both risk-averse and ambiguity-averse. However, in order to focus on ambiguity, the current example is a simplification in which we have a risk-neutral but ambiguity-averse investor.

[7] Consider a risk-averse decision maker with the utility function $\mathrm{U}(c) = 2\sqrt{c}$. In this case, the value (in terms of expected utility) of the option on the less risky asset is $C = 0.5 \times 2 \times \sqrt{120 - 100} = 4.47$, while the value of the option on the more risky asset is $C = 0.5 \times 2 \times \sqrt{130 - 100} = 5.48$.

event. Similarly to the certainty equivalent outcome (concerning risk), the perceived probability of the preferable payoff is approximated by $\mathrm{E}[\varphi(H)] \times \left(1 + \frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)} \mathrm{Var}[\varphi(H)]\right)$, where $-\frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)}$ is the coefficient of (constant absolute) ambiguity aversion.[8] Assume first an ambiguity-neutral decision maker. The ambiguity preference of this decision maker is characterized by a linear function $\Upsilon(\cdot)$, implying that perceived probabilities are equal to the expected probabilities. Accordingly, the value of the option (in terms of expected utility) remains the same and equal to $C = 0.5 \times (120 - 100) = 10$.

Now assume instead an ambiguity-averse decision maker with a constant absolute ambiguity aversion $-\frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)} = \eta = 2$. Due to aversion to ambiguity, this decision maker does not form perceived probabilities through a linear compounding of probabilities, but aggregates probabilities in a non-linear way as described above. As a result, the value of the option (in terms of expected utility) becomes $C \approx 0.5 \times (1 - 2 \times 0.01) \times (120 - 100) = 9.8$.[9] For a decision maker with higher aversion to ambiguity, say $\eta = 4$, the value of the option (in terms of expected utility) drops even further to $C \approx 0.5 \times (1 - 4 \times 0.01) \times (120 - 100) = 9.6$. Thus, an increase in aversion to ambiguity *decreases* the option value.

Assume now that the ambiguity of the project increases. For example, if future outcomes are distributed either $(0.3, 0.7)$ or $(0.7, 0.3)$ with equal likelihoods, then the expected probability of the good (and the bad) state remains unchanged: $\mathrm{E}[\varphi(H)] = 0.5 \times 0.3 + 0.5 \times 0.7 = 0.5$, but the variance of its probabilities increases to $\mathrm{Var}[\varphi(H)] = 0.5 \times (0.3 - 0.5)^2 + 0.5 \times (0.7 - 0.5)^2 = 0.04$, implying a degree of ambiguity of $\mho^2[X] = 0.04$. Assuming a coefficient of ambiguity aversion $\eta = 2$, the value of the option then drops to $C \approx 0.5 \times (1 - 2 \times 0.04)(120 - 100) = 9.2$.

This simple example illustrates our main predictions. An increase in risk (variance of outcomes) increases the value of the real option, hence increasing the investment in innovation. In contrast, an increase in ambiguity decreases option value, leading to a lower investment in innovation.

2.4 Hypotheses

Following this intuition, we propose three hypotheses.

Hypothesis 1 *Investments in innovation are higher for higher degrees of firm (project) risk.*

[8] See Equation (11) in Appendix A.

[9] When the decision maker is risk-averse with the utility function $\mathrm{U}(c) = 2\sqrt{c}$, the value (in terms of expected utility) is $C \approx 0.5 \times (1 - 2 \times 0.01) \times 2 \times \sqrt{120 - 100} = 4.38$.

This hypothesis coincides with Schwartz (2004). Contrary to the effect of risk, a higher ambiguity implies lower perceived probabilities of the good states—a successful R&D, and therefore a lower value of the option. A lower value of the real option results in less investment in R&D.

Hypothesis 2 *Investments in innovation are lower for higher degrees of firm (project) ambiguity.*

Moreover, we expect that the effect of ambiguity on innovation may depend on firm size. Specifically, in relative terms, ambiguity should matter more for small firms. Large firms have a history of projects and returns, and hence a probability distribution can be assessed more accurately for most types of R&D projects the firm undertakes. However, for small firms, with very little history as guidance, assessing accurately the probability distribution of outcomes is more difficult, and therefore small firms are more sensitive to ambiguity.

Hypothesis 3 *The effect of ambiguity on innovation is stronger for small firms than for large firms.*

Below we test these hypotheses on R&D and patent data. Although both R&D and patents reflect innovative activity by the firm, they measure innovation at different points in the life of the firm. R&D in principle precedes patent applications. As discussed, our stylized model of real options under risk and ambiguity applies in principle to an "investment project". However, in innovating firms, the main source of risk and ambiguity would be the innovative activity, rather than say, routine maintenance. The accounting treatment of R&D (expending) seems to recognize that R&D buys you an option, rather than a known asset that needs to be depreciated, as is the case for CAPEX expenditures. Because of that, and because of the nature of R&D vs. CAPEX, we focus on the former in our analysis.[10]

3 Data

The primary data sources for the analysis are the National Bureau of Economic Research (NBER) patent database for historical information on innovation output; intraday trade and quote (TAQ) data for the estimation of the degree of ambiguity; the Chicago Center for Research in Security Prices (CRSP) for the estimation of firm risk; and Compustat for accounting data.

[10]We also run regressions with CAPEX as the dependent variable, and find the effect of ambiguity to be negative, similar to the effect of R&D (untabulated results).

3.1 Sample construction

To construct our sample, we start with the sample of all firms covered by the NBER Patent Data Project (PDP). The PDP covers all patents granted by 2006, for both public and private firms. PDP provides an assignee number (*pdpass*) for each firm granted a patent, based on the original assignee number provided by the United States Patent and Trademark Office (USPTO). For public firms, the assignee number is then matched to a Compustat identifier (*gvkey*). As noted by Hall et al. (2001), a single organization can correspond to multiple *gvkeys* in Compustat, both in the same year (the parent and a subsidiary can have different *gvkeys*) and across time (when reorganization of the ownership structure can generate a different *gvkey*). To identify multiple *gvkeys* for a single firm and over time, PDP provides a new firm identifier (*pdpco*). The match between Compustat *gvkeys* and *pdpcos* in PDP includes both firms with matched patents and firms without patents. Therefore, we construct our dataset starting with the Compustat Fundamentals Annual file, augmented with *pdpco* identifiers, and then we discard *gvkeys* that are not used in PDP. These are typically subsidiaries, and another *gvkey* is matched to the patent data for that firm.

While using the *pdpco* firm identifier allows us to account for reorganizations that lead to a change in *gvkey*, we also attempt to identify firm reorganizations that are not accompanied by a change in *gvkey*. Specifically, following Bloom et al. (2013), whenever we observe extremely large jumps (greater than 200% or lower than -67%) in sales, employment, or assets, we treat the firm as a new entity and assign it a new identifier (*new gvkey*), even if the Compustat *gvkey* remains the same. Similarly, we assign a new firm identifier whenever we observe a gap in the data, either because the firm does not appear in Compustat in that year, or because one of our variables of interest is missing. This approach is more general than including a full set of *gvkey* fixed effects, because it allows the fixed effect to change over time, when the firm undergoes major changes.

As most other papers on patents, our measure of the patenting process is patent applications. However, patent applications are observed only conditional on the patent being eventually granted. Therefore, since our data ends in 2006, we are missing patents applied for in the later years of our sample period, but granted after 2006. Dass et al. (2017) document changes in the historical application-grant lag distribution, which render its use to correct for truncation problematic. Therefore, Dass et al. (2017) recommend dropping 3-5 years at the end of the sample. For this reason, we drop the last 4 years of the patent data, and we end the sample in 2002. Second, patent citations are subject to truncation, because we only observe citations of patents granted by 2006. To correct for this bias, we adjust the citation count for each patent using the weight provided in the PDP database (*hjtwt*). This weight is based on a quasi-structural econometric model for the citation lag distribution, which includes cited year, citing year and technology class effects (Hall et al., 2001)[11].

We use the historical SIC code to identify industries; when the historical SIC code is missing in Compustat, we use the historical SIC code from CRSP. When both are missing, we use the SIC code of the largest business or operating segment from the Compustat Segment Files. We exclude utilities (SIC codes 4900-4999), financials (SIC codes 6000-6999), public service, international affairs firms and non-operating establishments (SIC codes 9000-9999). We exclude all firm-years for a *pdpco* that is identified as a utility, financial, or public service firm in at least one year.

The sample starts in 1994 because our ambiguity measure, calculated from TAQ data, is available since 1993 and we use lagged ambiguity as an explanatory variable in our regressions. As explained above, the sample ends in 2002 because the NBER Patent dataset includes patents granted until 2006 and the last four years are subject to a severe truncation bias due to the application-grant lag (Dass et al., 2017).

Since the paper analyzes the effect of ambiguity on both innovation input (R&D investment) and intermediate output (patenting activity), we present empirical results for four samples: the *Full Sample*, the sample of firms with at least one year of positive R&D expenditures (*R&D Sample*), the sample of firms with at least one patent application (*Patent Sample*), and the sample of firms with at least one citation (*Citation Sample*), conditional on non-missing data for all variables of interest during the sample period (1994-2002). For the *Patent Sample* and the *Citation Sample*, we also require firms to have two years of patent data before the first year in the sample (the presample period). For firms that enter Compustat after 1994, we use the first two years of data as the presample period, and we include the following years in the sample.[12] For all samples, we require firms to have at least two years with nonmissing data. There are 14,641 firm-years for 3,010 different

[11]In Hall et al. (2001) the base (omitted) category for cited year effects is 1963-64, and the base (omitted) technological field category is *Other*, a catchall category which includes all patents except for those in Chemicals, Computers and Communications, Drugs and Medical, Electrical and Electronics. Hence, in addition to correcting for citation truncation, the *hjtwt* variable in PDP also implicitly converts the citation count for a patent to a common unit, which is one citation for a patent in the "Other" category granted in 1963 or 1964.

[12]See the discussion of the Blundell et al. (1999) presample mean scaling fixed effect estimator in Section 3.5.

gvkeys (3,187 *new gvkeys*) in the *Full Sample*, 7,880 firm-years for 1,538 different *gvkeys* (1,593 *new gvkeys*) in the *R&D Sample*, 7,416 firm-years for 1,366 different *gvkeys* (1,405 *new gvkeys*) in the *Patent Sample*, and 7,050 firm-years for 1,286 different *gvkeys* (1,319 *new gvkeys*) in the *Citation Sample*. The *R&D* and *Patent* samples do not overlap completely: only 5,943 firm-years are in both samples, while 1,937 firm-years are only in the *R&D Sample*, and 1,473 firm-years are only in the *Patent Sample*.[13]

3.2 Measures of innovation

We analyze two measures of investment in innovation: RD_SALES and RD_ASSETS, and two measures of intermediate innovation output: PATENTS (the number of patents applied for during a given year, conditional on being granted by 2006) and CITATIONS (the total number of citations received by these patents, corrected for citation truncation using the *hjtwt* variable in the NBER Patent Database). We winsorize the two measures of innovation input (RD_SALES and RD_ASSETS) at the top 1% over all firm-years.

Recent papers classify patents as either exploitative or exploratory, depending on the extent to which they rely on prior knowledge or on new knowledge (e.g., Liu et al., 2017). In Appendix B, we discuss this issue and present results for our sample.

3.3 Estimating ambiguity

To proxy for the ambiguity associated with a firm, we estimate the ambiguity of its equity. Intuitively, ambiguity represents the uncertainty in future outcome *probabilities*, as opposed to risk, which measures the uncertainty in future *outcomes*. We employ the empirical method used by Izhakian and Yermack (2017) to estimate the degree of ambiguity using intraday stock trading data from the TAQ database.

To this end, we assume the existence of a representative agent with a set of priors over the intraday return distributions. The observed intraday returns on the underlying asset are assumed to be a realization of one specific prior. That is, every day is characterized by a different distribution of returns, and the set of these distributions over a month represents the agent's set of priors.[14]

[13] The fact that almost 20% of firm-years in the *Patent Sample* do not have positive R&D expenditures during the sample period is consistent with Koh and Reeb (2015), who find that a significant number of firms with missing R&D in Compustat actually file and receive patents.

[14] The set of priors of the representative agent reflects the aggregation of all agents' identical sets of priors.

Assuming that stock returns are normally distributed, the degree of ambiguity of the return on equity r_j can be measured by

$$\mho^2 [r_j] = \int \mathrm{E}\left[\phi\left(r_j;\mu_j,\sigma_j\right)\right] \mathrm{Var}\left[\phi\left(r_j;\mu_j,\sigma_j\right)\right] dr_j, \tag{1}$$

where $\phi(r_j;\mu_j,\sigma_j)$ stands for the normal probability density function of r_j, conditional upon the mean μ_j and the variance σ_j^2. It is important to recall that the degree of ambiguity, measured by $\mho^2[\cdot]$, accounts for the uncertainty (ambiguity) about the mean and the variance (volatility), as well as for the uncertainty about all higher moments of the probability distribution (i.e., skewness, kurtosis, etc.) through the variance of probabilities.

To estimate the set of possible probability distributions of returns using the TAQ data, we sample the price of the stock every five minutes starting from 9:30 until 16:00. The decision to use five-minute time intervals is motivated in part by Andersen et al. (2001), who show that this time interval is sufficient to eliminate microstructure effects. In cases in which there is no trade at a specific time interval, we take the volume-weighted average of the closest trading prices. Using these prices, we compute five-minute returns, resulting in a maximum of 78 intraday returns on any given day. We ignore returns between closing and next-day opening prices, thereby eliminating the impact of overnight price changes and dividend distributions. For each stock, we drop all trading days with less than 10 different five-minute time intervals, and we drop all trading months with less than 10 intra-day return distributions. In addition, we drop extreme returns based on extreme price movements (plus or minus 10 percent returns) within five minutes, as many of them are due to mistaken orders that were cancelled by the stock exchange.

For a given stock, for each day, we compute the normalized (by the number of intraday observations) mean μ_j and variance σ_j^2 of the returns. As in French et al. (1987), the variance of the returns is computed by applying the adjustment for non-synchronous trading, proposed by Scholes and Williams (1977).[15] Based upon the assumption that the intraday returns are normally distributed, for each stock j we construct the set of priors $\mathcal{P}_j$, where each prior P_j within the set $\mathcal{P}_j$ is defined by a pair of μ_j and σ_j.

The set $\mathcal{P}_j$ of (normal) probability distributions of each stock j for a given month consists of 10 to 22 different probability distributions. To compute the monthly degree of ambiguity of a given

[15] The Scholes and Williams (1977) adjustment for non-synchronous trading suggests that the volatility of returns takes the form $\sigma_t^2 = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(r_{t,i} - \mathrm{E}\left[r_{t,i}\right]\right)^2 + 2\frac{1}{N_t - 1}\sum_{i=2}^{N_t}\left(r_{t,i} - \mathrm{E}\left[r_{t,i}\right]\right)\left(r_{t,i-1} - \mathrm{E}\left[r_{t,i-1}\right]\right)$.

asset, specified in Equation (1), we represent each daily return distribution by a histogram. To this end, we divide the range of daily returns, from -40% to 40%, into 160 intervals (bins), each of width 0.5%. For each day, we compute the probability of the return being in each bin. In addition, we compute the probability of the return being lower than -40% and the probability of the return being higher than 40%. Using these probabilities, we compute the mean and the variance of probabilities for each of the 162 bins separately, assigning equal weights to each probability distribution in the set $\mathcal{P}_j$ (i.e., all histograms are equally likely). This is equivalent to assuming that the daily ratios $\frac{\mu_j}{\sigma_j}$ are student's-t distributed.[16] Then, we estimate the degree of ambiguity of each stock j for each month by the discrete form

$$\mho^2[r_j] = \frac{1}{\sqrt{w(1-w)}} \times \left(\begin{array}{l} \mathrm{E}\left[\Phi\left(r_{j,0};\mu_j,\sigma_j\right)\right]\mathrm{Var}\left[\Phi\left(r_{j,0};\mu_j,\sigma_j\right)\right]+ \\ \sum_{i=1}^{160}\mathrm{E}\left[\Phi\left(r_{j,i};\mu_j,\sigma_j\right)-\Phi\left(r_{j,i-1};\mu_j,\sigma_J\right)\right]\mathrm{Var}\left[\Phi\left(r_{j,i};\mu_j,\sigma_j\right)-\Phi\left(r_{j,i-1};\mu_j,\sigma_j\right)\right]+ \\ \mathrm{E}\left[1-\Phi\left(r_{j,160};\mu_j,\sigma_j\right)\right]\mathrm{Var}\left[1-\Phi\left(r_{j,160};\mu_j,\sigma_j\right)\right] \end{array} \right),$$

where $\Phi(\cdot)$ stands for the cumulative normal probability distribution, $r_{j,0} = -0.40$, $w = r_{j,i} - r_{j,i-1} = 0.005$, and $\frac{1}{\sqrt{w(1-w)}}$ scales the weighted-average volatilities of probabilities to the bins' size. This scaling, which is analogous to Sheppard's correction, has been tested to verify that it minimizes the effect of the selected bin size on the values of $\mho^2$.[17]

Finally, $\mathrm{AMBIGUITY_t}$, our measure of ambiguity in year t, is the average over all months of monthly ambiguity $\mho^2[r_j]$ during year t. We require at least six months of ambiguity data in order to calculate the annual ambiguity measure $\mathrm{AMBIGUITY_t}$.

3.4 Estimating risk

Along with ambiguity, risk serves as the most important explanatory variable in our analysis. Our measure of risk is the variance of daily returns adjusted for dividends obtained from the CRSP

[16] When $\frac{\mu}{\sigma}$ is Student's t-distributed, cumulative probabilities are uniformly distributed. See, for example, Proposition 1.27 on p.21 in Kendall and Stuart (2010). This is consistent with the idea that the representative decision maker does not have any information indicating which of the possible probability distributions is more likely, and thus acts as if he assigns an equal weight to each possibility.

[17] Brenner and Izhakian (2017) and Augustin and Izhakian (2016) formally rule out the concern that $\mho^2$ may capture other well-known "uncertainty" factors including skwness, kurtosis, variance of variance, variance of mean, downside risk, mixed data sampling measure of forecasted volatility (MIDAS), investors' sentiment, jumps, among several others. Their tests also rule out the concern that observed returns are generated by a single (additive) probability distribution. This is confirmed in Table 2, which shows a weak correlation of thirty percent between ambiguity and risk.

database. Since probabilities are uncertain, risk can be viewed as computed using the expected probabilities of outcomes. For each individual stock j in a given month m, we calculate the variance, $Var_{j,m}$, of the stock's daily returns over that month, again applying the Scholes and Williams (1977) correction for non-synchronous trading and a correction for heteroscedasticity.[18]

$\mathrm{RISK_t}$, our measure of risk in year t, is the average over all months of monthly risk $Var_{j,m}$ during year t. We require at least six months of data in order to calculate the annual risk measure $\mathrm{RISK_t}$.

3.5 Control variables

We control for variables that are known to be correlated with innovation. Our controls include: ILLIQUIDITY, LN_SALES, ROA, Q, LEVERAGE, LN_K_L (where K_L is the ratio of physical capital per employee), LN_AGE, a dummy for Nasdaq listing, a dummy for missing R&D expenditures in Compustat, and LN_RDCAP (the log of R&D capital). All variables are defined in Appendix C.

Our proxy for investment opportunities is the total Q, calculated following Peters and Taylor (2017). Whereas the standard approach in the literature is to divide the market value of assets by the book value of total assets from the balance sheet (Compustat item *at*), Peters and Taylor (2017) propose a measure that accounts for the internal intangible capital, ie the capitalized investment in intangible capital not reflected in the balance sheet (R&D investment and the investment in organizational capital). We follow this approach, which is in line with our focus on innovation and intangible investment. Nevertheless, we test our hypotheses with the traditional Q measure and the results are similar.

We control for Nasdaq listing for two reasons. First, Nasdaq firms tend to be young and highly innovative, and therefore with possibly higher ambiguity, which directly affects our dependent variables. Second, by including an indicator variable for Nasdaq firms, we control for trading differences that potentially affect the explanatory variables constructed from trading data (AMBIGUITY, RISK and ILLIQUIDITY).[19]

[18] See, for example, French et al. (1987).

[19] As pointed out by Amihud (2002), the volume of trading has a different meaning for Nasdaq firms than for NYSE/AMEX firms. On Nasdaq, during most of our sample period, the trading was done almost entirely through market makers, and each trade with a market maker, as well as trades between market makers, were counted separately. This results in inflated volumes of trading for Nasdaq firms, which directly affects ILLIQUIDITY. In order to deal with the inflated volume for Nasdaq firms, we follow Gao and Ritter (2010) and divide it by 2 prior to February

We omit firm-years with AMBIGUITY, RISK or ILLIQUIDITY below the 1st percentile and above the 99th percentile over the entire sample period. We winsorize K_L at the top 1% and ROA the top and bottom 1%. Following Lanjouw and Schankerman (2004), Aghion et al. (2013) and others, we winsorize Q by setting it equal to 0.10 for values below 0.10 and to 20 for values above 20. All balance sheet and income statement variables are deflated using the annual GDP deflator from St Louis Fed (2009=100).

3.6 Summary statistics

Table 1 presents descriptive statistics for the *R&D Sample* (Panel A) and the *Patent Sample* (Panel B). For brevity, descriptive statistics for the *Full Sample* and the *Citation Sample* are presented in the Appendix Table IA1. Each panel presents statistics for all firms, as well as for large and small firms within that sample, where large firms are firms above the median in terms of sales, and small firms are below the median.

The median firm in the *R&D Sample* has annual sales of $399 million, while for the *Patent Sample*, the median firm is much larger, with sales of $779 million. The median age, approximated by the number of years in Compustat, is 12 years in the *R&D Sample*, and 16 years in the *Patent Sample*. Overall these differences suggest that R&D investment and patenting may take place at different stages in the firms life cycle[20]. In the *R&D Sample* the median RD_SALES is 5.8% (the mean is 16%). In Panel A, we also note that 3.2% of the firm-years in the *R&D Sample* have missing R&D (for the *Full Sample* 33.1% of the firm-years have missing R&D). Conditional on filing at least one patent across all sample years (*Patent Sample*, Panel B), the median firm files 3 patents per year and receives 22.644 citations. The distribution of the number of patents and citations is heavily skewed in all panels, as has been previously documented.

The median AMBIGUITY in the *R&D Sample* (Panel A) is 0.052. Given that AMBIGUITY measures the expected variance of probabilities, this implies that the median expected standard

1, 2001, by 1.8 for February 1, 2001 to December 31, 2001, and by 1.6 for 2002 and 2003. According to Gao and Ritter (2010), no adjustment to trading volume is necessary for Nasdaq firms after 2003. Therefore, including an indicator variable for Nasdaq firms in the regression accounts for the effect of trading differences not already accounted for by the Gao and Ritter (2010) correction.

[20]However, part of the difference in age between the *R&D Sample* and the *Patent Sample* comes from the fact that, for firms that start to be covered by Compustat (broadly speaking, IPO firms) during the sample period, we use the first two years of data to construct presample means of the dependent count variables (PATENTS and CITATIONS), effectively removing these years from the actual sample, such that the minimum age in the *Patent Sample* is 2 years.

deviation of probabilities is $\sqrt{0.052} = 22.8\%$. The median RISK of 0.022 per month corresponds to an annualized stock return volatility of approximately $\sqrt{12 \times 0.022} = 51.38\%$.

Comparing the subsamples of large and small firms within each sample, the most relevant for our paper is that the distribution of AMBIGUITY differs according to firm size. As expected, AMBIGUITY is higher for small firms than for large firms. Also, AMBIGUITY seems to vary much more in the small firm subsample than in the large firm subsample. For example, in the *R&D Sample* (Panel A), the interquartile range for ambiguity is only 0.059-0.023=0.036 for large firms (Panel A2), but 0.309-0.037=0.272 for small firms (Panel A3). We observe the same pattern in the *Full Sample*, the *Patent Sample*, and the *Citation Sample*. Given the little variation in AMBIGUITY for large firms, it will be difficult to find a significant effect in this sub-sample, or if we do find an effect, it could be driven by extreme values.[21]

Table 2 Panel A presents Pearson (below the diagonal) and Spearman (above the diagonal) correlation coefficients for the explanatory variables for all firms in the *R&D* and *Patent Samples*. The correlation between AMBIGUITY and RISK is 0.31 in both samples. Similarly, AMBIGUITY is positively correlated with ILLIQUIDITY (correlation of 0.381 in the *R&D Sample* and 0.474 in the *Patent Sample*), and negatively correlated with size (correlation of -0.499 with LN_SALES in the *R&D Sample* and -0.469 in the *Patent Sample*). Similar patterns and magnitudes for correlations are observed in the other three samples.

In Table 2 Panel B, we present correlations for selected variables for subsamples of large firms and small firms. It appears that the correlations between AMBIGUITY and the other variables from Panel A are driven by small firms, while a completely different picture emerges for large firms. First, in the *R&D Sample*, the Pearson correlation between AMBIGUITY and RISK (0.318 unconditionally), is negative -0.124 for large firms, and 0.173 for small firms (Panel B1). In the *Patent Sample*, the wedge between large and small firms increases: the Pearson correlation between AMBIGUITY and RISK is -0.227 for large firms and 0.252 for small firms.

Second, AMBIGUITY is negatively correlated with LN_SALES in subsamples of small firms (Pearson correlation of -0.431 in the *R&D Sample* and -0.505 in the *Patent Sample*). For large firms, however, the two variables are positively correlated (Pearson correlation of 0.178 in the *R&D*

[21] For RISK, the interquartile range in the *R&D Sample* is 0.021-0.006=0.015 for large firms (Panel A2) and 0.056-0.023=0.033 for small firms (Panel A3).

Sample and 0.326 in the *Patent Sample*)[22]. The same patterns of correlations for large and small firms hold if we use either LN_ASSETS or LN_MCAP, instead of LN_SALE, as proxies for firm size.[23]

4 Empirical methodology

First, to analyze the effect of ambiguity on innovation input, we estimate the following model using OLS:

$$RD_{it+1} = \alpha + \beta_1 AMBIGUITY_{i,t} + \beta_2 RISK_{i,t} + \Gamma' X_{i,t} + \mu_i + \nu_t + \epsilon_{i,t}, \quad (2)$$

where $RD_{i,t+1}$ is either RD_SALES or RD_ASSETS for firm i in year $t+1$; $X_{i,t}$ is a vector of control variables; μ_i denotes firm fixed effects; and ν_t denotes year fixed effects. Standard errors are clustered by firm. The coefficient estimates for this model are presented in Tables 3, 4 and 5.

Second, we estimate the following count models:

$$\mathrm{E}\left[PAT_{i,s,t+n}|X_{i,t}, \xi_s, \chi_i, \nu_t\right] = \exp\left(\alpha + \beta_1 AMBIGUITY_{i,t} + \beta_2 RISK_{i,t} + \Gamma' X_{i,t} + \xi_s + \chi_i + \nu_t\right), \quad (3)$$

where $\mathrm{E}\left[.\right]$ stands for expected value; $PAT_{i,s,t+n}$ is either $PATENTS_{i,s,t+n}$ or $CITATIONS_{i,s,t+n}$ for firm i, in industry s and year $t+n$ ($n = 1, 2, 3$); $X_{i,t}$ is a vector of control variables; ξ_s denotes industry (3-digit SIC code) fixed effects; χ_i denotes Blundell et al. (1999) presample firm fixed effects; and ν_t denotes year fixed effects. Standard errors are clustered by firm. Equation (3) is estimated using both a Poisson and a Negative Binomial model. Estimation results are presented in Tables 6, 7 and 8.

In the count models for PATENTS and CITATIONS, we follow the recent innovation literature (Aghion et al., 2013, Bloom et al., 2013, and others), and control for unobserved, time-invariant, firm-level heterogeneity using the pre-sample mean scaling fixed effect estimator of Blundell et al. (1999). This approach exploits the history of patent data for each firm and uses the log of presam-

[22] Without conditioning on R&D or patenting activity, the Pearson correlation between AMBIGUITY and RISK for large firms is only 0.038 (see the Appendix Table IA2 Panel B1)

[23] Given the low variation in AMBIGUITY for large firms documented in Table 1, any correlation between AMBIGUITY and other variables in this subsample could be driven by outliers. Spearman rank correlations (reported above the diagonal in Table 2 Panel B) demonstrate that the patterns of correlations between AMBIGUITY on one hand and RISK and LN_SALES on the other hand are not driven by outliers. The correlation between AMBIGUITY and ILLIQUIDITY for large firms is an exception (positive Pearson correlation and negative Spearman correlation).

ple averages of the count dependent variable as a proxy for unobserved heterogeneity. We calculate presample means of the dependent count variables starting in 1975, to create a variable that characterizes the firm in question. We require firms to have at least two years of pre-sample data in order to calculate pre-sample averages of the dependent variables. For firms that enter Compustat after 1994 (the first year of data in our sample), we use the first two years of data to calculate pre-sample averages, and we include the following years in the sample.[24]

In addition to the presample mean scaling fixed effect, the models in Tables 6, 7 and 8 include three-digit SIC code fixed effects and year fixed effects. We use three-digit SIC codes instead of four-digit SIC codes because our sample includes both NYSE/AMEX and Nasdaq firms, and, according to WRDS documentation, CRSP provides only the three-digit SIC code for Nasdaq firms (adding a 0 for the fourth digit for these firms).

Patent data tend to have excess zeroes compared to the standard Poisson or Negative Binomial distributions (Greene, 1994). There are two types of models that account for excess zeros: zero-inflated and hurdle models. Both models are called two-part models because they consist of one binary (typically logit) model and one count model (Poisson or Negative Binomial). The difference between these two types of models is that in a zero-inflated regression both models contribute zeros, while in a hurdle regression zero values come entirely from the binary part of the model, while positive values come from a zero-truncated count model. For example, in a hurdle model for the number of patents, the binary model can be interpreted as the extensive margin—modeling the probability of innovating versus not innovating, while the zero-truncated count model can be interpreted as the intensive margin—the number of patents conditional on having at least one patent (see Belloc et al., 2016, for this interpretation).[25]

We estimate the following hurdle negative binomial model:

$$\mathrm{P}\left(PAT_{i,s,t+n} = j | X_{i,t}, \xi_s, \chi_i, \nu_t\right) = \begin{cases} \varphi_1\left(0\right) & \text{if } j = 0 \\ \frac{1-\varphi_1(0)}{1-\varphi_2(0)}\varphi_2\left(j\right) & \text{if } j > 0, \end{cases} \tag{4}$$

where $\mathrm{P}\left(.\right)$ stands for probability; $PAT_{i,s,t+n}$ is either $PATENTS_{i,s,t+n}$ or $CITATIONS_{i,s,t+n}$ for firm i, in industry s and year $t+n$ ($n = 1, 2, 3$); $X_{i,t}$ is a vector of control variables; ξ_s denotes

[24] Bloom et al. (2013) use a similar approach, requiring 4 years of presample data in their dataset covering the 1981-2001 period.

[25] If, instead, an innovative firm that could potentially patent decides to not patent its innovations, then a zero-inflated model is theoretically more appropriate.

Moskowitz and Grinblatt (1999) fixed effects; χ_i denotes Blundell et al. (1999) presample firm fixed effects; ν_t denotes year fixed effects; $\varphi_1(0)$ is the probability of a zero count from a logit model in which the odds ratio of a positive count versus a zero count is:

$$\exp\left(\alpha_1 + \beta_{1,1} AMBIGUITY_{i,t} + \beta_{1,2} RISK_{i,t} + \Gamma_1{}' X_{i,t} + \xi_s + \chi_i + \nu_t\right)$$

and $\varphi_2(j)$ is the probability of observing a positive count equal to j, based on the negative binomial distribution with:

$$\mathrm{E}\left[PAT_{i,s,t+n} | X_{i,t}, \xi_s, \chi_i, \nu_t\right] = \exp\left(\alpha_2 + \beta_{2,1} AMBIGUITY_{i,t} + \beta_{2,2} RISK_{i,t} + \Gamma_2' X_{i,t} + \xi_s + \chi_i + \nu_t\right)$$

In the hurdle negative binomial equations, whenever a coefficient has two subscripts, the first subscript denotes the equation, as follows: 1 refers to coefficients from the logit part of the model, and two 2 refers to coefficients from the negative binomial part of the model. Standard errors are clustered by firm. The estimation results are presented in Table 6.

In hurdle negative binomial models, we include industry fixed effects using the Moskowitz and Grinblatt (1999) 20 industry classification, based on SIC codes.[26] The reason we use a coarser industry classification for the hurdle models is that we run into convergence problems when trying to use finer classifications, including two-digit SIC codes.[27] For robustness, we estimate our standard negative binomial regressions from Table 6 using Moskowitz and Grinblatt (1999) industry fixed effects, two-digit and three-digit SIC industry fixed effects, as well as Fama-French 48 industry fixed effects, and the coefficients on AMBIGUITY are similar (in terms of both sign and significance) across the different industry classifications, while the coefficients on RISK vary depending on the industry fixed effects used and on the left-hand side variable[28].

[26] The Moskowitz and Grinblatt (1999) industry classification has also been used in the innovation literature by Dong et al. (2016).

[27] We estimate the hurdle negative binomial models using the hnblogit command in Stata.

[28] Table 6, columns (4)-(6) and (10)-(12) present estimation results for the negative binomial model using three-digit SIC industry fixed effects, and Table 9 Panels A and B, columns (1)-(3) presents estimation results for the same model using Moskowitz and Grinblatt (1999) industry fixed effects. Results using two-digit SIC code fixed effects and Fama-French 48 industry fixed effects are not tabulated. Overall, in the negative binomial models for CITATIONS, RISK is positive and significant for any industry classification coarser than three-digit SIC codes (e.g. Table 9 Panel B, columns (1)-(3)).

5 Results

5.1 Innovation input

Table 3 presents coefficient estimates for OLS regressions for R&D investment as a function of lagged AMBIGUITY, controlling for lagged RISK and other explanatory variables. We present regression results for both the *R&D Sample* and the *Full Sample*. By construction, any effect on R&D investment is driven by firms with at least one year of positive R&D expenditures (the *R&D Sample*, and this effect will be mitigated in the *Full Sample*. For both samples, we find that AMBIGUITY has a negative and significant effect on R&D investment scaled by sales (RD_SALES). We do not find a significant effect of AMBIGUITY on RD_ASSETS. The effect of RISK is not significant in this model.

In Table 4, we conduct a subsample analysis for the regressions in Table 3. We find that the effect of AMBIGUITY is driven essentially by firms at an early stage of their development—small firms, NASDAQ firms, and young firms. Lagged RISK is positive and significant for large firms (column 1), but is not significant for small firms (column 2). Interestingly, unconstrained firms rather than constrained firms seem to be marginally more affected by ambiguity. One potential explanation is that older firms are constrained as well. An alternative explanation is that the Kaplan-Zingales index may not measure what we need to measure for our purposes. Farre-Mensa and Ljungqvist (2016) point out that the standard measures of financial constraints, such as the Kaplan-Zingales index, the Whited-Wu index, the Hadlock-Pierce index, or an indicator for paying a dividend or having a credit rating do a poor job in terms of identifying financially constrained firms. However, the overall message seems fairly clear—that small firms, where ambiguity is higher, indeed invest less in R&D as ambiguity increases, as our model predicts, but large firms, where ambiguity is lower, seem to "care" more about risk, invest more when risk increases, consistent with the predictions of our real options framework.

In Table 5, we conduct several robustness tests for the subsample analysis presented in Table 4. First, we exclude firm-years with sales less than $20m (Panel 1). Second, we exclude firm-years with stock price below $5 at the end of the previous year (Panel 2). Third, we exclude very young firms, i.e. firms with less than 5 years in Compustat (Panel 3). Overall, lagged AMBIGUITY remains negative and significant for small firms in all panels. For the subsample of young firms (column 8), the effect of AMBIGUITY is driven mainly by very small firms and penny stocks, as AMBIGUITY is no longer significant in Table 5, Panels 1 and 2.[29][30]

5.2 Innovation output

5.2.1 Patents and citations

Table 6 presents results for Poisson and Negative Binomial regressions for PATENTS (columns 1-6) and CITATIONS (columns 7-12). All regressions include three-digit SIC code fixed effects, Blundell et al. (1999) presample firm fixed effects, and year fixed effects. Panel 1 presents estimated coefficients and Panel 2 presents marginal effects for lagged AMBIGUITY and RISK when moving from the 10th to the 90th percentile of the variable of interest and keeping all the other regressors at their sample means.

Table 6, Panel 2 thus shows that, in the Poisson model, the predicted number of patents three years ahead at the 10th percentile of lagged AMBIGUITY in the *Patent Sample* (0.015, see Table 1 Panel B1) is 5.922, while the predicted number of patents at the 90th percentile of lagged AMBIGUITY (0.266) is 3.376. The marginal effect of AMBIGUITY is thus to decrease the predicted number of patents by 2.546, and this effect is statistically significant at the 1% level. Similarly, the predicted number of citations[31] received for patents filed three years ahead is 45.941 at the 10th percentile of lagged AMBIGUITY, but only 30.340 at the 90th percentile of lagged AMBIGUITY. The marginal effect is -15.601 citations, and is statistically significant at the 5% level.

Overall, Table 6 shows that AMBIGUITY has a negative and significant effect on both PATENTS and CITATIONS up to three years into the future. Both the significance and the magnitudes are lower in the Negative Binomial models, but AMBIGUITY is always negative and remains significant in year $t+3$. These marginal effects are economically important, given that the median (mean)

[29] All our results are robust to controlling for the probability of gain, GAINPROB, defined as the probability that the return is higher than the risk-free rate, and computed assuming that returns are normally distributed. Given the low variability in this variable documented in Table 1, we present our results without including GAINPROB in our regressions.

[30] The results on R&D investment, presented in Tables 3, 4 and 5 are similar if we extend the sample period to include more recent data. In untabulated analysis, we run these regressions with data up to 2015 and obtain results very close to those presented in the paper. We report the results for the sample ending in 2002 in order to use the same sample period for R&D investment as for patents and citations.

[31] Recall that the one unit for citations adjusted using the *hjtwt* variable from NBER is one citation received by a patent in the *Other* technological category (one of the 6 technological categories defined by Hall et al. (2001)), filed in 1963 or 1964.

firm in the *Patent Sample* files 3 (31.183) patent applications during a sample year and receives 22.644 (423.622) citations for these patents (Table1 Panel B).

The effect of RISK on patenting activity in Table 6 is less clear and depends on both the horizon and the econometric model. Specifically, coefficients are positive in the Poisson models for all horizons and negative in the Negative Binomial models for years $t + 1$ and $t + 2$ for PATENTS, while for CITATIONS the positive and significant coefficients for all years in the Poisson models (columns 7-9) become insignificant in the Negative Binomial models (columns 10-12).[32].

Next we explore the effect of AMBIGUITY on PATENTS and CITATIONS across subsamples of large and small firms (Table 7). Again, the negative effect of AMBIGUITY is driven by the subsample of small firms, while the positive effect of RISK is driven by the subsample of large firms. The fact that AMBIGUITY is not significant for large firms is not surprising given the low variability of our ambiguity measure in this subsample. Compared to Table 6, we also notice that RISK is consistently positive and significant for large firms in year $t + 3$ in both the Poisson and the Negative Binomial model.

Table 8 presents two robustness tests for our results. First, we exclude from the sample firm-years at the top 5% of the patent distribution, for the PATENT models, or at the top 5% of the citation distribution, for the CITATION models. Panel 1 shows that the effect of AMBIGUITY does not change when we exclude highly successful (blockbuster) innovators. However, the effect of RISK in the PATENT equation is no longer significant (compare the coefficients on RISK in columns 1-3 and 7-9 in Table 7 and Table 8). This suggests that the effect of RISK in the PATENT equation is driven by blockbuster firms,[33] while the effect of AMBIGUITY is driven by firms with a more moderate patenting activity.

A second concern is that, given the negative correlation between AMBIGUITY and LN_SALES for small firms documented in Table 2, the negative effect of AMBIGUITY on innovation could be driven by very small firms that do not patent. To address this concern, we exclude firm-years with sales less than $20m (Table 8 Panel 2). In fact, the coefficients on AMBIGUITY for small firms increase in magnitude compared to Table 6, and even in significance (see the effect on CITATIONS in year $t + 2$, column 11), suggesting that the effect is not driven by very small firms.

[32] As pointed out in footnote 28, in the negative binomial models for CITATIONS, risk is positive and significant for any industry classification coarser than 3-digit SIC codes.

[33] However, note that the effect of RISK on CITATIONS is positive and significant for large firms whether we exclude blockbuster firms (Table 8) or not (Table 7)

The effects of AMBIGUITY and RISK on PATENTS and CITATIONS are robust to excluding firm-years with stock price less than \$5 at the end of the previous year (Table IA4 Panel 1), firm-years with less than 5 years in Compustat (Table IA4 Panel 2), and to controlling for the probability of gain, GAINPROB (Table IA4 Panel 3).

In a final robustness test, we ran all our regressions controlling for the log number of SIC codes from the Compustat Segment files, and the results are very similar to those reported in the paper. This suggests that the differential results for small and large firms are not explained by the fact that large firms are more likely to be diversified.

5.2.2 Excess zeroes

To account for excess zeroes, we estimate hurdle negative binomial models for both PATENTS (Table 9 Panel A) and CITATIONS (Table 9 Panel B) for all firms, and across size subsamples (Panel C). Each model includes Moskowitz and Grinblatt (1999) industry fixed effects, Blundell et al. (1999) presample firm fixed effects, and year fixed effects. As discussed in Section 4, we use the Moskowitz and Grinblatt (1999) industry fixed effects (consisting of 20 industries) in the hurdle negative binomial model, because we cannot achieve convergence using a finer industry classification. We are, however, reassured by the fact that the effect of AMBIGUITY in the standard Negative Binomial regression with Moskowitz and Grinblatt (1999) industry fixed effects (Table 9, Panels A and B, columns 1-3) is similar to that from a standard Negative Binomial regression with the same explanatory variables, but including 3-digit SIC code fixed effects (Table 6 columns 4-6 and 10-12). This suggests that the effect of AMBIGUITY is not explained by unobserved industry heterogeneity not accounted for by Moskowitz and Grinblatt (1999) industry fixed effects.

Table 9 Panel A reveals that AMBIGUITY has a negative and significant effect in the Logit equation for patents filed in year $t+1$ (the extensive margin). As well, the effect in the Zero-Truncated Negative Binomial equation (the intensive margin) is negative and significant for all horizons. For CITATIONS (Panel B), lagged AMBIGUITY is significant only in the Logit equation, for year $t+3$. Finally, the effect of AMBIGUITY is driven mostly by the subsample of small firms (Panel C).

6 Conclusion

One of the most important questions in innovation research is the effect of uncertainty on investment in R&D and in patents, which by definition are paths into the unknown. We suggest that reality may be more nuanced, with different types of uncertainty (risk and ambiguity) leading to very different firm decisions. Some recent papers have documented the response of investment in innovation to specific factors. We focus on the distinction between risk and ambiguity as drivers of innovation.

To support our hypotheses, we present a stylized model, which shows that firms increase investment in innovative projects as risk increases, but decrease investment as ambiguity goes up. Empirically, we document an interesting duality. Our findings suggest that small firms may be much more concerned with the effects of ambiguity, whereas large firms, with a proven track record, view risk as the uncertainty dimension of interest. We document a negative effect of ambiguity on innovation input (R&D investment), as well as on intermediate innovation output (patents and citations) for small firms. We do not find a significant effect of ambiguity on innovation for large firms, perhaps because there is not much variation in our ambiguity measure in this subsample. At the same time, we find a positive effect of risk on innovation output for large firms, but the effect of risk on the number of patents is driven by firms in the top 5% of the patent distribution. These results demonstrate that ambiguity and risk capture separate dimensions of uncertainty, which affect innovation in different ways for different types of firms.

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A Theoretical Appendix

A.1 Decision Theoretic Model of Ambiguity

To formally define the uncertain payoff X in EUUP framework, let $(\mathcal{S}, \mathcal{E}, \mathrm{P})$ be a probability space, where $\mathcal{S}$ is a state space, $\mathcal{E}$ is a σ-algebra of subsets of the state space (i.e., a set of events), $\mathrm{P} \in \mathcal{P}$ is a probability measure, and the set of probability measures $\mathcal{P}$ is convex. An algebra Π of measurable subsets of $\mathcal{P}$ is equipped with a probability measure, denoted ξ. The uncertain outcome is then given by the uncertain variable, $X : \mathcal{S} \to \mathbb{R}$. Denote by $\varphi(x)$ the (uncertain) marginal probability (density function or probability mass function) associated with the (uncertain) cumulative probability $\mathrm{P} \in \mathcal{P}$ of outcome x. The expected marginal and cumulative probability of outcome x, taken using the second-order probability measure ξ, are then respectively defined by

$$\mathrm{E}[\varphi(x)] \equiv \int_{\mathcal{P}} \varphi(x)\, d\xi \qquad \text{and} \qquad \mathrm{E}[\mathrm{P}(x)] \equiv \int_{\mathcal{P}} \mathrm{P}(x)\, d\xi, \tag{5}$$

and the variance of the marginal probability of outcome x is defined by

$$\mathrm{Var}[\varphi(x)] \equiv \int_{\mathcal{P}} \big(\varphi(x) - \mathrm{E}[\varphi(x)]\big)^2 d\xi. \tag{6}$$

With these definitions in place, the expected outcome and the variance of outcomes are computed using the expected probabilities. That is,

$$\mathbb{E}[X] \equiv \int \mathrm{E}[\varphi(x)]\, x dx \qquad \text{and} \qquad \mathbb{V}\mathrm{ar}[X] \equiv \int \mathrm{E}[\varphi(x)] \big(x - \mathbb{E}[x]\big)^2 dx. \tag{7}$$

Notice that double-struck capital font designates expectation or variance of outcomes with respect to expected probabilities, while regular straight font designates expectation or variance of probabilities with respect to second-order probabilities.

Investors have distinct preferences concerning risk and ambiguity. As usual, preferences concerning risk are modeled by a bounded, strictly-increasing and twice-differentiable utility function $\mathrm{U} : \mathbb{R}_+ \to \mathbb{R}$. Risk aversion takes the form of a concave $\mathrm{U}(\cdot)$, risk loving takes the form of a convex $\mathrm{U}(\cdot)$, and risk neutrality takes the form of a linear $\mathrm{U}(\cdot)$. Like Tversky and Kahneman's (1992) cumulative prospect theory, EUUP assumes that investors have a reference point, relative to which returns are classified as either unfavorable (loss) or favorable (gain). Accordingly, we normalize U to $\mathrm{U}(k) = 0$, where k is the investors' reference point.

As investors are sensitive to ambiguity, they do not compound the set of priors $\mathcal{P}$ and the prior ξ over $\mathcal{P}$ in a linear way (compounded lotteries), but instead they aggregate these probabilities in a non-linear way that reflects their aversion to ambiguity. Preferences concerning ambiguity are defined by preferences over mean-preserving spreads in probabilities and modeled by a strictly-increasing and twice-differentiable function over probabilities, $\Upsilon : \mathbb{R}_+ \to \mathbb{R}$, called the *outlook function*. Similar to risk, ambiguity aversion takes the form of a concave $\Upsilon(\cdot)$, ambiguity loving takes the form of a convex $\Upsilon(\cdot)$, and ambiguity neutrality takes the form of a linear $\Upsilon(\cdot)$. In EUUP, ambiguity aversion is exhibited when an investor prefers the expectation of an uncertain probability of each payoff over the uncertain probability itself.[34]

Suppose that the decision to save one unit of wealth is made at the beginning of the period, and the outcome, which is the only source of wealth, occurs at end of the period. In EUUP, the

[34]Recall that risk aversion is exhibited when an investor prefers the expected outcome of the uncertain outcome over the uncertain outcome itself.

expected utility of this investment opportunity can be approximated by[35]

$$\mathrm{W}(X) \approx \int_{x\leq k} \mathrm{U}(x) \underbrace{\mathrm{E}[\varphi(x)]\left(1 - \frac{\Upsilon''(1-\mathrm{E}[\mathrm{P}(x)])}{\Upsilon'(1-\mathrm{E}[\mathrm{P}(x)])}\mathrm{Var}[\varphi(x)]\right)}_{\text{Perceived Probability of Unfavorable Outcome}} dx + \int_{x\geq k} \mathrm{U}(x) \underbrace{\mathrm{E}[\varphi(x)]\left(1 + \frac{\Upsilon''(1-\mathrm{E}[\mathrm{P}(x)])}{\Upsilon'(1-\mathrm{E}[\mathrm{P}(x)])}\mathrm{Var}[\varphi(x)]\right)}_{\text{Perceived Probability of Favorable Outcome}} dx. \tag{8}$$

Notice that when investors are ambiguity neutral (i.e., $\Upsilon(\cdot)$ is linear), investors compound probabilities linearly and Equation (8) collapses to the conventional expected utility. In contrast, when investors are ambiguity-averse (i.e., $\Upsilon(\cdot)$ is concave), they do not aggregate probabilities linearly and the intensity of aversion to ambiguity affects the perceived probabilities. In this case, investors overweight the probabilities of the unfavorable outcomes and underweight the probabilities of favorable outcomes. Conceptually, the perceived probability of a given outcome is the unique certain probability values that the investor is willing to accept in exchange for its uncertain probability (i.e., a certainty-equivalent probability).

The notion of mean-preserving spreads in probabilities in Equation (8) can be used to derive a measure of ambiguity (Izhakian, 2016, Theorem 6). This measure, defined as the expected variance of probabilities, is formally given by

$$\mho^2[X] \equiv \int \mathrm{E}[\varphi(x)]\,\mathrm{Var}[\varphi(x)]\,dx. \tag{9}$$

The measure $\mho^2$ (mho^2) can be used either in a continuous state space with infinitely many outcomes or in a discrete state space with finitely many outcomes.

To observe the distinct impact of ambiguity and ambiguity aversion on the value of an investment opportunity, consider a binomial asset with either low payoff (L) or high payoff (H). Suppose that the reference point k satisfies $L \leq k \leq \mathbb{E}[X] < H$.[36] By Equation (8), the value of this asset in

[35] This functional representation is obtained by taking the Taylor expansion of the dual representation of EUUP, proposed by Izhakian (2017). The remainder of this approximation is of order $o\big(\int \mathrm{E}\left[|\varphi(x) - \mathrm{E}[\varphi(x)]|^3\right] x dx\big)$ as $\int |\varphi(x) - \mathrm{E}[\varphi(x)]|\, dx \to 0$, meaning that the accuracy of the approximation is equivalent to the accuracy of the cubic approximation, $o\left(\mathbb{E}\left[|x - \mathbb{E}[x]|^3\right]\right)$, in which the fourth and higher absolute central moments of outcomes are of strictly smaller order than the third absolute central moment as $|x - \mathbb{E}[x]| \to 0$, and are therefore negligible.

[36] We assume that the expected outcome is greater than the reference point; otherwise, a rational decision maker would not consider the investment opportunity.

terms of expected utility is

$$\begin{aligned}\mathrm{W}(X) \quad &\approx \quad \mathrm{U}(L)\,\mathrm{E}[\varphi(L)]\left(1-\frac{\Upsilon''(1-\mathrm{E}[\mathrm{P}(H)])}{\Upsilon'(1-\mathrm{E}[\mathrm{P}(H)])}\mathrm{Var}[\varphi(L)]\right)+ \\ &\quad\;\; \mathrm{U}(H)\,\mathrm{E}[\varphi(H)]\left(1+\frac{\Upsilon''(\mathrm{E}[\mathrm{P}(H)])}{\Upsilon'(\mathrm{E}[\mathrm{P}(H)])}\mathrm{Var}[\varphi(H)]\right).\end{aligned} \tag{10}$$

Expected utility in this functional representation is assessed using the investor's perceived probabilities. Ambiguity and ambiguity aversion are modeled in Equation (10) through the investor's marginal perceived probabilities. Consider the high payoff, H. The expression

$$\mathrm{Q}(H) \quad \approx \quad \mathrm{E}[\varphi(H)]\left(1+\frac{\Upsilon''(\mathrm{E}[\mathrm{P}(H)])}{\Upsilon'(\mathrm{E}[\mathrm{P}(H)])}\mathrm{Var}[\varphi(H)]\right) \tag{11}$$

is the marginal perceived probability of this outcome occurring.[37] This marginal perceived probability is a function of the degree of ambiguity, measured by $\mathrm{Var}[\varphi(H)]$, and the investor's attitude toward ambiguity, captured by $-\frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)}$. For an ambiguity-averse investor with $-\frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)} > 0$, a higher aversion to ambiguity or a higher degree of ambiguity results in lower marginal perceived probabilities of good states and higher marginal perceived probabilities of bad states. This in turn implies a lower perceived expected utility.

A.2 Stylized model

To support our hypotheses about the effect of ambiguity and risk on investment decisions, we employ the EUUP framework to develop a stylized static model. We investigate the effect of risk and ambiguity on innovation decisions in the lens of real options. In this view, an R&D investment or a patent filing can be considered as a real option. Suppose that I is the present value of the costs of developing the product, and V is the present value of the expected cash flows from this development. The payoff X from owning a product can then be written

$$X \quad = \quad \begin{cases} V-I, & \text{if} \quad V \geq I; \\ 0, & \text{if} \quad V < I. \end{cases}$$

Thus, by Schwartz (2004), the project can be viewed as a call option, where the net payoff of the product itself is the underlying asset.

Assume a one period model with zero risk-free rate. Suppose that the cost of developing a product using the technology is the reference point, i.e., $k = I$, satisfying $0 \leq k$. By Equation (8),

[37] Note that, since every $\mathrm{P} \in \mathcal{P}$ is additive, $1-\mathrm{E}[\mathrm{P}(L)] = \mathrm{E}[\mathrm{P}(H)]$. In this case, the variance of the probabilities of L is equal to the variance of the probabilities of its complementary event H, so that $\mathrm{Var}[\varphi(L)] = \mathrm{Var}[\varphi(H)]$.

the value of this (call) option is

$$C \;\approx\; \int_I^\infty \mathrm{E}\left[\varphi\left(x\right)\right]\left(1+\frac{\Upsilon''\left(\mathrm{E}\left[\mathrm{P}\left(x\right)\right]\right)}{\Upsilon'\left(\mathrm{E}\left[\mathrm{P}\left(x\right)\right]\right)}\mathrm{Var}\left[\varphi\left(x\right)\right]\right)xdx. \tag{12}$$

As in Rothschild and Stiglitz (1970), an underlying security is said to become riskier if its new payoffs can be written as a mean-preserving spread of the old payoffs. Accordingly, we assume neither that risk is measured by the variance of payoffs, nor that that returns are normally distributed or that the utility is quadratic. Equation (12) suggests that the option value is increasing in the risk of the payoff of the project, since the option payoff function is convex in the state outcomes. To see this more clearly, consider a possible payoff x of the project. Assume that the risk of the project increases, such that this specific payoff is now $x+\Delta$ or $x-\Delta$, with equal probabilities, i.e. $x\pm\Delta$ is a mean-preserving spread of x. Since the reference point satisfies $k=I$, the value of the call option is positively affected by the magnitude of Δ: when $\Delta \leq x-I$ the option value is unaffected, and when $\Delta > x-I$, then $\frac{1}{2}\left(x-I+\Delta\right) \geq x$. Thus, by Equation (12), the value of the option increases in the risk of the project.[38]

In addition to the effect of risk, a higher ambiguity implies lower perceived probabilities of the good states—a successful R&D, and therefore a lower value of the option. To see this, in Equation (12), consider for example an ambiguity-averse attitude of the CAAA type. In this case $-\frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)}=\eta$, where η is the coefficient of absolute ambiguity aversion. Since aversion to ambiguity implies a positive $-\frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)}$, a higher ambiguity, measured by $\mho^2\left[X\right]$ (which in this case is equal to the weighted sum of $\mathrm{Var}\left[\varphi\left(x\right)\right]$), implies lower perceived probabilities (Equation (11)) and therefore a lower value of the option. A lower value of the real option results in less investment in R&D.

B The Effect of Ambiguity on Innovation Style

We also analyze two dimensions of innovation style: "exploitative" or "exploratory". Following Liu et al. (2017), we define a patent as exploitative if 60% or more of the patents it cites are part of the firm's prior knowledge. A firm's prior knowledge at the beginning of year t is the knowledge contained in the patents previously filed by the firm (prior patents), and in the patents cited by the firm's prior patents. Similarly, a patent is defined as exploratory if 40% or less of the patents it cites

[38]Note that, assuming normally distributed returns, a quadratic utility function or an exponential utility function (all imply a mean-variance-ambiguity preference), risk can be measured by the variance of returns, computed using expected probabilities (Izhakian and Yermack, 2017).

are part of the firm's prior knowledge. EXPLOIT is the percentage of exploitative patents, and EXPLORE is the percentage of exploratory patents filed during a given year. When calculating EXPLOIT and EXPLORE, we use the *pdpco* variable from the NBER Patent Database to identify a firm over time, in other words we assume that technological knowledge is transferred when the firm is undergoing a reorganization, whether or not it leads to a change in *gvkey* in Compustat.

Table IA5 presents estimated coefficients from OLS regressions of EXPLOIT and EXPLORE on lagged AMBIGUITY, controlling for lagged RISK and other firm characteristics. The results indicate that a higher AMBIGUITY leads firms to adopt a more exploratory innovation style, instead of relying on prior knowledge.

We do not find a significant effect of AMBIGUITY or RISK on patent originality or generality, nor on the average Akcigit et al. (2016) distance from the firm's prior patents.

C Variable Definitions

Variable	Definition
AGE	Number of years in Compustat, counted from the first year the *pdpco* appears in Compustat. *pdpco* is the firm identifier in the NBER Patent Database, defined starting with the Compustat *gvkey* and modified to account for reorganizations that result in changes in *gvkey*.
AMBIGUITY	The annual average of monthly ambiguity, where monthly ambiguity is defined as in Equation (9). We require monthly ambiguity to be available for at least six months during the year.
ASSETS	Compustat item *at*.
CITATIONS	The number of citations received by all patents applied for in a given year, adjusted for citation truncation using the variable *hjtwt* from the NBER Patent Database (Hall et al., 2001).
EXPLOIT	The percentage of exploitative patents applied for in a given year. A patent is defined to be exploitative if at least 60% of the citations it makes refer to the firm's prior knowledge. We assume that the firm's prior knowledge consists the set of all patents filed by the firm (*pdpco*) in the previous years (prior patents), as well as all patents cited by the firm's prior patents (Sørensen and Stuart, 2000, Katila and Ahuja, 2002, Liu et al., 2017).
EXPLORE	The percentage of exploratory patents applied for in a given year. A patent is defined to be exploratory if less than 40% of the citations it makes refer to the firm's prior knowledge. We assume that the firm's prior knowledge consists the set of all patents filed by the firm (*pdpco*) in the previous years (prior patents), as well as all patents cited by the firm's prior patents (Sørensen and Stuart, 2000, Katila and Ahuja, 2002, Liu et al., 2017).

GAINPROB	The probability of gain, estimated as the probability of the return being higher than the risk-free rate, computed assuming that returns are normally distributed.
ILLIQUIDITY	Amihud (2002) illiquidity measure. The annual average of $\|r_{id}\|/(prc_{id} \times vol_{id})$, where r_{id} is the return on stock i on day d, prc_{id} is the closing price of stock i on day d and vol_{id} is the trading volume. We adjust the trading volume for Nasdaq firms by dividing it by 2 prior to February 1, 2001, by 1.8 for February 1, 2001 to December 31, 2001, and for 1.6 for 2002 and 2003 (Gao and Ritter, 2010). We require at least 100 trading days during the year in order to calculate ILLIQUIDITY.
K_L	The ratio of physical capital per employee. Compustat item *ppent* divided by Compustat item *emp*
KZINDEX	Kaplan-Zingales index. $-1.001909 \times ((ib + dp)/\text{lagged } ppent) + 0.28226389 \times ((at + prcc\_f \times csho - ceq - txdb$ (replaced with zero when missing)$/at) + 3.139193 \times ((dltt + dlc)/(dltt + dlc + seq)) - 39.3678 \times ((dvc + dvp)/\text{lagged } ppent) - 1.314759 \times (che/\text{lagged } ppent)$
LEVERAGE	$(dltt + dlc)/at$
LN_AGE	$ln(1 + AGE)$
LN_ASSETS	$ln(ASSETS)$
LN_K_L	$ln(1 + K\_L)$
LN_MCAP	$ln(MCAP)$
LN_PRECITATIONS	$ln(1 + PRECITATIONS)$
LN_PREPATENTS	$ln(1 + PREPATENTS)$
LN_RDCAP	$ln(1 + RDCAP)$
LN_SALES	$ln(SALES)$
MCAP	Market capitalization. Compustat item $prcc\_f \times csho$
NASDAQ	Indicator variable equal to 1 if the stock is traded on Nasdaq at the end of the year, and 0 otherwise.

OCAP	The stock of organizational capital. The investment in organizational capital (30% of SG&A expenditures), capitalized using a perpetual inventory model with a depreciation rate $\delta_{SG\&A} = 20\%$. SG&A expenditures are equal to the Compustat item *xsga* less R&D expenditures when these are likely to be included in *xsga*. Following Peters and Taylor (2017), we assume that R&D expenditures less in-process R&D (Compustat item *xrd* + *xrd*) are included in *sga*, unless *xrd* + *xrd* is greater than *sga* and lower than *cogs*, in which case R&D expenditures are likely to be included in the COGS, rather than in SG&A expenses. When calculating OCAP, we fill missing *sga* in Compustat with interpolated values.
PATENTS	The number of patents applied for during the year.
PRECITATIONS	The annual average of the number of citations received for patents applied for during the presample period. (See the definition of PREPATENTS.)
PREPATENTS	The annual average of the number of patents applied for during the presample period (Blundell et al., 1999). We use the entire history of patent data starting in 1975 as the presample period. Recall that our sample starts in 1994 (because we include $\text{AMBIGUITY}_{\text{t-1}}$ in our regressions and AMBIGUITY is only available since 1993). For firms that enter Compustat after 1994, we use the first two years of data as the presample period, and we start the sample with the third year in Compustat. The presample period starts in 1975 or the first year when the firm appears in the dataset (whichever occurs last) and ends one year before the first sample year. The first sample year is either 1994 or the third year the firm enters Compustat (whichever occurs last).
Q	Total Q. Calculated following Peters and Taylor (2017) as $(csho \times prcc\_f - ceq - txdb$ (replaced with zero when missing) $+ at)/(at + RDCAP + OCAP)$.
RD_ASSETS	The ratio of R&D expenditures (Compustat item *xrd*, replaced with zero when missing) to assets (Compustat item *at*).
RD_SALES	The ratio of R&D expenditures (Compustat item *xrd*, replaced with zero when missing) to sales (Compustat item *sale*).

RDMISS	An indicator variable equal to 1 if *xrd* is missing in Compustat, and 0 otherwise.
RDCAP	R&D capital stock. R&D expenditures, capitalized using the perpetual inventory model: $$G_{it} = (1 - \delta_{R\&D}) \times G_{it-1} + R\&D_{it}$$ with a depreciation rate $\delta_{SG\&A} = 15\%$ and $G_{i0} = R\&D_{i0}/\delta_{R\&D}.$, which assumes that the firm has been investing at the rate $R\&D_{it}$ forever (Falato et al., 2013). When calculating RDCAP, we fill missing *xrd* in Compustat with interpolated values.
RISK	The annual average of the monthly variance of stock returns. The monthly variance of stock returns is the variance, $Var_{i,m}$, of stock's daily returns over that month, applying the Scholes and Williams (1977) correction for non-synchronous trading and a correction for heteroscedasticity (see for example French et al., 1987). We require the monthly variance of stock returns to be available for at least six months during the year.
ROA	Return on assets. $oibdp/at$.
SALES	Compustat item *sale*.

Table 1: Descriptive Statistics

The table presents descriptive statistics for the variables used in the analysis. The sample period is 1994-2002. The *R&D Sample* (Panel A) consists of all firms with at least two years of data for all variables of interest and least one year of positive R&D expenditures in Compustat during the sample period. The *Patent Sample* consists of all firms with at least two years in the presample period, two years of data for all variables of interest and at least one patent application filed during the sample period. For each sample, descriptive statistics are presented for all firms (e.g. Panel A1), for large firms (e.g. Panel A2) and for small firms (e.g. Panel A3). Large (small) firms are those with sales above (below) the sample median for NYSE/AMEX/NASDAQ firms in year t. Sample construction is explained in detail in Section 3.1. For variable definitions see Appendix C.

A1: R&D Sample - All Firms

Variable	N	Mean	St. Dev.	Min	10th Pct.	25th Pct.	Median	75th Pct.	90th Pct.	Max
AMBIGUITY_t	7,880	0.124	0.162	0.007	0.015	0.026	0.052	0.148	0.364	0.844
RISK_t	7,880	0.031	0.031	0.001	0.005	0.010	0.022	0.041	0.067	0.253
ILLIQUIDITY_t	7,880	0.220	1.055	0.000	0.001	0.004	0.026	0.150	0.491	51.319
GAINPROB_t	7,880	0.502	0.030	0.284	0.465	0.483	0.501	0.520	0.539	0.636
SALES_t	7,880	3,041.303	12,207.610	0.466	31.174	89.198	398.567	1,787.332	6,158.686	220,506.100
ASSETS_t	7,880	3,297.648	17,020.050	3.142	41.330	95.181	389.799	1,711.047	6,145.697	386,814.800
MCAP_t	7,880	4,149.961	14,319.610	3.715	71.727	163.472	547.434	2,155.817	7,134.364	252,050.600
RDCAP_t	7,880	647.819	3,026.883	0.000	10.406	30.763	86.135	272.668	1,007.151	60,235.960
ROA_t	7,880	0.099	0.200	-1.841	-0.121	0.067	0.142	0.201	0.262	0.445
Q_t	7,880	1.581	1.284	0.146	0.660	0.887	1.209	1.798	2.855	20.000
LEVERAGE_t	7,880	0.175	0.179	0.000	0.000	0.013	0.137	0.281	0.405	1.000
KZINDEX_t	7,880	-4.978	17.944	-859.705	-12.223	-5.187	-1.546	0.353	1.614	72.427
K_L_t	7,880	56.681	86.588	0.399	11.889	19.749	33.038	61.241	114.835	1,535.646
AGE_t	7,880	18.329	15.585	1.000	3.000	6.000	12.000	31.000	45.000	51.000
NASDAQ_t	7,880	0.548	0.498	0.000	0.000	0.000	1.000	1.000	1.000	1.000
RDMISS_{t+1}	7,880	0.032	0.176	0.000	0.000	0.000	0.000	0.000	0.000	1.000
RD_SALES_{t+1}	7,880	0.160	0.451	0.000	0.005	0.018	0.058	0.144	0.272	5.093
RD_ASSETS_{t+1}	7,880	0.094	0.109	0.000	0.006	0.019	0.058	0.131	0.225	0.625
PATENTS_{t+1}	7,880	29.317	117.258	0.000	0.000	0.000	2.000	11.000	56.000	2,579.000
CITATIONS_{t+1}	7,880	399.067	1,894.859	0.000	0.000	0.000	13.538	135.105	628.609	61,310.880

Table 1: Descriptive Statistics

A2: R&D Sample - Large Firms

Variable	N	Mean	St. Dev.	Min	10th Pct.	25th Pct.	Median	75th Pct.	90th Pct.	Max
$AMBIGUITY_t$	3,940	0.051	0.053	0.007	0.015	0.023	0.037	0.059	0.094	0.779
$RISK_t$	3,940	0.016	0.017	0.001	0.003	0.006	0.011	0.021	0.036	0.194
$ILLIQUIDITY_t$	3,940	0.026	0.133	0.000	0.000	0.001	0.004	0.015	0.046	4.059
$GAINPROB_t$	3,940	0.500	0.027	0.370	0.466	0.482	0.498	0.516	0.534	0.630
$SALES_t$	3,940	5,960.677	16,763.920	398.842	552.022	842.004	1,787.332	4,741.718	12,132.280	220,506.100
$ASSETS_t$	3,940	6,459.397	23,652.110	114.612	471.763	788.891	1,707.217	4,517.728	12,462.950	386,814.800
$MCAP_t$	3,940	7,971.608	19,511.490	22.457	393.529	836.263	2,037.490	5,592.725	17,506.350	252,050.600
$RDCAP_t$	3,940	1,229.653	4,200.373	0.000	28.492	86.576	246.712	744.003	2,188.729	60,235.960
ROA_t	3,940	0.166	0.081	-0.248	0.077	0.120	0.162	0.209	0.264	0.445
Q_t	3,940	1.466	1.086	0.286	0.756	0.928	1.185	1.625	2.355	20.000
$LEVERAGE_t$	3,940	0.237	0.171	0.000	0.018	0.111	0.226	0.330	0.440	1.000
$KZINDEX_t$	3,940	-2.332	6.474	-194.423	-6.954	-3.627	-1.141	0.442	1.520	16.850
K_L_t	3,940	76.024	111.430	1.698	17.964	26.784	43.381	80.939	158.193	1,535.646
AGE_t	3,940	27.204	16.383	1.000	5.000	11.000	29.000	44.000	48.000	51.000
$NASDAQ_t$	3,940	0.232	0.422	0.000	0.000	0.000	0.000	0.000	1.000	1.000
$RDMISS_{t+1}$	3,940	0.046	0.209	0.000	0.000	0.000	0.000	0.000	0.000	1.000
RD_SALES_{t+1}	3,940	0.051	0.068	0.000	0.003	0.009	0.024	0.064	0.141	1.561
RD_ASSETS_{t+1}	3,940	0.047	0.056	0.000	0.003	0.010	0.026	0.063	0.123	0.605
$PATENTS_{t+1}$	3,940	55.639	161.436	0.000	0.000	1.000	7.000	39.000	126.000	2,579.000
$CITATIONS_{t+1}$	3,940	746.133	2,629.351	0.000	0.000	0.000	65.547	380.319	1,589.707	61,310.880

Table 1: Descriptive Statistics

A3: R&D Sample - Small Firms

Variable	N	Mean	St. Dev.	Min	10th Pct.	25th Pct.	Median	75th Pct.	90th Pct.	Max
AMBIGUITY_t	3,940	0.198	0.197	0.007	0.015	0.037	0.125	0.309	0.496	0.844
RISK_t	3,940	0.045	0.035	0.002	0.014	0.023	0.036	0.056	0.088	0.253
ILLIQUIDITY_t	3,940	0.414	1.460	0.001	0.017	0.041	0.131	0.373	0.903	51.319
GAINPROB_t	3,940	0.504	0.031	0.284	0.465	0.483	0.503	0.525	0.543	0.636
SALES_t	3,940	121.929	103.228	0.466	16.900	38.881	89.198	181.463	290.773	398.293
ASSETS_t	3,940	135.899	128.797	3.142	25.736	49.319	95.181	180.604	303.780	2,007.243
MCAP_t	3,940	328.314	488.869	3.715	47.228	85.691	171.167	375.336	735.762	7,366.868
RDCAP_t	3,940	65.985	77.478	0.000	6.473	17.660	42.331	85.975	151.169	920.297
ROA_t	3,940	0.032	0.254	-1.841	-0.274	-0.063	0.100	0.188	0.258	0.445
Q_t	3,940	1.695	1.447	0.146	0.567	0.813	1.258	2.052	3.275	15.255
LEVERAGE_t	3,940	0.113	0.165	0.000	0.000	0.000	0.036	0.172	0.335	1.000
KZINDEX_t	3,940	-7.624	24.252	-859.705	-19.540	-7.911	-2.162	0.249	1.710	72.427
K_L_t	3,940	37.339	42.797	0.399	9.496	14.966	24.877	44.143	76.462	961.043
AGE_t	3,940	9.455	7.742	1.000	3.000	4.000	7.000	12.000	19.000	47.000
NASDAQ_t	3,940	0.863	0.344	0.000	0.000	1.000	1.000	1.000	1.000	1.000
RDMISS_{t+1}	3,940	0.018	0.133	0.000	0.000	0.000	0.000	0.000	0.000	1.000
RD_SALES_{t+1}	3,940	0.269	0.615	0.000	0.017	0.055	0.118	0.216	0.472	5.093
RD_ASSETS_{t+1}	3,940	0.142	0.127	0.000	0.018	0.053	0.110	0.188	0.308	0.625
PATENTS_{t+1}	3,940	2.995	7.421	0.000	0.000	0.000	0.000	3.000	8.000	140.000
CITATIONS_{t+1}	3,940	52.000	165.633	0.000	0.000	0.000	0.000	35.956	138.978	3,362.462

Table 1: Descriptive Statistics

B1: Patent Sample - All Firms

Variable	N	Mean	St. Dev.	Min	10th Pct.	25th Pct.	Median	75th Pct.	90th Pct.	Max
AMBIGUITY$_t$	7,416	0.098	0.136	0.007	0.015	0.025	0.046	0.097	0.266	0.840
RISK$_t$	7,416	0.025	0.026	0.001	0.004	0.008	0.017	0.033	0.056	0.249
ILLIQUIDITY$_t$	7,416	0.139	0.636	0.000	0.001	0.002	0.014	0.084	0.314	39.813
GAINPROB$_t$	7,416	0.500	0.029	0.284	0.465	0.482	0.499	0.518	0.537	0.630
SALES$_t$	7,416	3,873.927	13,431.810	0.495	49.509	181.842	779.081	2,654.470	8,506.711	234,484.600
ASSETS$_t$	7,416	4,010.204	17,576.170	3.142	63.168	173.840	677.447	2,551.297	8,217.001	386,814.800
MCAP$_t$	7,416	5,129.603	16,555.950	4.814	97.727	242.286	828.128	3,079.837	10,065.900	310,071.700
RDCAP$_t$	7,416	657.163	3,111.476	0.000	0.000	11.848	71.897	271.298	1,033.844	60,235.960
ROA$_t$	7,416	0.122	0.171	-1.841	-0.028	0.092	0.149	0.203	0.263	0.445
Q$_t$	7,416	1.538	1.178	0.154	0.688	0.901	1.203	1.754	2.676	20.000
LEVERAGE$_t$	7,416	0.197	0.176	0.000	0.000	0.036	0.177	0.305	0.420	1.000
KZINDEX$_t$	7,416	-3.934	13.777	-328.112	-9.869	-4.210	-1.197	0.505	1.509	72.427
K_L$_t$	7,416	67.248	121.319	0.399	13.459	21.870	35.336	67.848	135.278	1,535.646
AGE$_t$	7,416	21.563	15.861	2.000	4.000	7.000	16.000	36.000	46.000	51.000
NASDAQ$_t$	7,416	0.446	0.497	0.000	0.000	0.000	0.000	1.000	1.000	1.000
RDMISS$_{t+1}$	7,416	0.198	0.398	0.000	0.000	0.000	0.000	0.000	1.000	1.000
RD_SALES$_{t+1}$	7,416	0.129	0.432	0.000	0.000	0.004	0.033	0.113	0.218	5.093
RD_ASSETS$_{t+1}$	7,416	0.072	0.100	0.000	0.000	0.004	0.033	0.103	0.186	0.625
PATENTS$_{t+1}$	7,416	31.183	120.362	0.000	0.000	0.000	3.000	12.000	61.000	2,579.000
CITATIONS$_{t+1}$	7,416	423.622	1,949.678	0.000	0.000	0.000	22.644	153.465	678.744	61,310.880
EXPLOIT$_{t+1}$	5,408	0.272	0.292	0.000	0.000	0.000	0.200	0.447	0.667	1.000
EXPLORE$_{t+1}$	5,408	0.613	0.331	0.000	0.083	0.370	0.625	1.000	1.000	1.000

Table 1: Descriptive Statistics

B2: Patent Sample - Large Firms

Variable	N	Mean	St. Dev.	Min	10th Pct.	25th Pct.	Median	75th Pct.	90th Pct.	Max
AMBIGUITY_t	3,708	0.049	0.041	0.007	0.017	0.025	0.039	0.059	0.089	0.562
RISK_t	3,708	0.014	0.015	0.001	0.003	0.005	0.009	0.017	0.031	0.194
ILLIQUIDITY_t	3,708	0.013	0.056	0.000	0.000	0.001	0.002	0.009	0.025	1.887
GAINPROB_t	3,708	0.500	0.027	0.407	0.468	0.483	0.498	0.516	0.534	0.630
SALES_t	3,708	7,495.222	18,291.880	779.233	969.918	1,411.565	2,654.470	6,523.518	16,294.000	234,484.600
ASSETS_t	3,708	7,757.220	24,285.120	217.935	776.991	1,233.712	2,548.874	6,404.541	16,407.560	386,814.800
MCAP_t	3,708	9,735.090	22,467.110	13.364	573.533	1,184.668	2,918.425	7,288.474	22,549.680	310,071.700
RDCAP_t	3,708	1,232.905	4,323.151	0.000	0.000	2.878	187.063	756.419	2,213.554	60,235.960
ROA_t	3,708	0.165	0.075	-0.231	0.084	0.119	0.160	0.205	0.257	0.445
Q_t	3,708	1.451	0.934	0.286	0.781	0.940	1.190	1.636	2.341	12.358
LEVERAGE_t	3,708	0.249	0.156	0.000	0.042	0.140	0.241	0.340	0.441	1.000
KZINDEX_t	3,708	-2.161	6.396	-194.423	-6.637	-3.359	-0.885	0.566	1.489	14.006
K_L_t	3,708	87.717	152.960	0.480	17.873	26.667	44.373	88.838	185.426	1,535.646
AGE_t	3,708	30.475	15.485	2.000	7.000	15.000	34.000	45.000	48.000	51.000
NASDAQ_t	3,708	0.155	0.362	0.000	0.000	0.000	0.000	0.000	1.000	1.000
RDMISS_{t+1}	3,708	0.264	0.441	0.000	0.000	0.000	0.000	1.000	1.000	1.000
RD_SALES_{t+1}	3,708	0.036	0.056	0.000	0.000	0.000	0.014	0.044	0.109	0.453
RD_ASSETS_{t+1}	3,708	0.033	0.046	0.000	0.000	0.000	0.015	0.044	0.100	0.318
PATENTS_{t+1}	3,708	57.566	165.709	0.000	0.000	1.000	7.000	40.000	134.000	2,579.000
CITATIONS_{t+1}	3,708	764.345	2,703.708	0.000	0.000	0.000	50.855	368.625	1,646.770	61,310.880
EXPLOIT_{t+1}	2,862	0.277	0.249	0.000	0.000	0.000	0.250	0.429	0.587	1.000
EXPLORE_{t+1}	2,862	0.596	0.288	0.000	0.231	0.391	0.588	0.826	1.000	1.000

Table 1: Descriptive Statistics

B3: Patent Sample - Small Firms

Variable	N	Mean	St. Dev.	Min	10th Pct.	25th Pct.	Median	75th Pct.	90th Pct.	Max
AMBIGUITY_t	3,708	0.147	0.175	0.007	0.013	0.025	0.066	0.210	0.410	0.840
RISK_t	3,708	0.036	0.030	0.001	0.009	0.016	0.028	0.045	0.071	0.249
ILLIQUIDITY_t	3,708	0.265	0.880	0.000	0.008	0.022	0.073	0.234	0.619	39.813
GAINPROB_t	3,708	0.501	0.031	0.284	0.463	0.481	0.501	0.522	0.539	0.616
SALES_t	3,708	252.633	219.551	0.495	24.546	65.397	181.842	402.619	611.727	778.928
ASSETS_t	3,708	263.187	267.811	3.142	38.003	77.457	173.840	382.555	577.132	2,850.809
MCAP_t	3,708	524.116	1,034.107	4.814	62.703	123.970	262.811	581.513	1,124.473	28,795.460
RDCAP_t	3,708	81.421	111.372	0.000	0.000	14.798	44.690	104.681	202.632	1,050.844
ROA_t	3,708	0.079	0.222	-1.841	-0.180	0.029	0.130	0.200	0.267	0.445
Q_t	3,708	1.625	1.374	0.154	0.611	0.841	1.228	1.894	2.996	20.000
LEVERAGE_t	3,708	0.144	0.179	0.000	0.000	0.002	0.071	0.239	0.389	1.000
KZINDEX_t	3,708	-5.707	18.234	-328.112	-13.777	-5.424	-1.546	0.420	1.554	72.427
K_L_t	3,708	46.779	72.151	0.399	11.088	17.894	29.182	51.193	93.436	1,535.646
AGE_t	3,708	12.652	10.226	2.000	3.000	5.000	9.000	16.000	29.000	51.000
NASDAQ_t	3,708	0.737	0.440	0.000	0.000	0.000	1.000	1.000	1.000	1.000
RDMISS_{t+1}	3,708	0.132	0.339	0.000	0.000	0.000	0.000	0.000	1.000	1.000
RD_SALES_{t+1}	3,708	0.223	0.594	0.000	0.000	0.019	0.083	0.172	0.364	5.093
RD_ASSETS_{t+1}	3,708	0.111	0.122	0.000	0.000	0.021	0.078	0.154	0.257	0.625
PATENTS_{t+1}	3,708	4.801	11.237	0.000	0.000	0.000	1.000	5.000	12.000	269.000
CITATIONS_{t+1}	3,708	82.899	247.451	0.000	0.000	0.000	11.109	66.323	206.494	5,089.890
EXPLOIT_{t+1}	2,546	0.267	0.334	0.000	0.000	0.000	0.111	0.500	0.875	1.000
EXPLORE_{t+1}	2,546	0.632	0.373	0.000	0.000	0.333	0.718	1.000	1.000	1.000

Table 2: Correlations

The table presents correlation coefficients for the variables used in the analysis. The *R&D Sample* consists of all firms with at least two years of data for all variables of interest and least one year of positive R&D expenditures in Compustat during the sample period. The *Patent Sample* consists of all firms with at least two years in the presample period, two years of data for all variables of interest and at least one patent application filed during the sample period. Panel A reports correlations for all firms in the *R&D Sample* (A1) and the *Patent Sample* (A2). Panel B reports selected correlations for large and small firms in each sample separately. The sample period is 1994-2002. Entries below the diagonal are Pearson correlations, and entries above the diagonal are Spearman correlations. Sample construction is explained in detail in Section 3.1. For variable definitions see Appendix C.

A. Correlations for All Firms

A1. R&D Sample

	AMBIGUITY$_t$	RISK$_t$	ILLIQUIDITY$_t$	GAINPROB$_t$	LN_SALES$_t$	ROA$_t$	Q$_t$	LEVERAGE$_t$	LN_K_L$_t$	LN_AGE$_t$	NASDAQ$_t$	RDMISS$_{t+1}$	LN_RDCAP$_t$
AMBIGUITY$_t$	1.000	0.116	0.616	-0.033	-0.419	-0.227	-0.198	-0.074	-0.196	-0.185	0.253	-0.007	-0.362
RISK$_t$	0.318	1.000	0.521	0.306	-0.648	-0.389	-0.025	-0.331	-0.299	-0.529	0.610	-0.095	-0.340
ILLIQUIDITY$_t$	0.381	0.216	1.000	0.038	-0.831	-0.398	-0.264	-0.219	-0.405	-0.492	0.544	-0.038	-0.706
GAINPROB$_t$	0.035	0.324	0.027	1.000	-0.094	-0.189	-0.129	-0.058	-0.001	-0.106	0.134	-0.027	0.012
LN_SALES$_t$	-0.499	-0.503	-0.237	-0.076	1.000	0.383	-0.040	0.437	0.373	0.613	-0.663	0.092	0.674
ROA$_t$	-0.380	-0.436	-0.155	-0.199	0.475	1.000	0.395	-0.025	0.104	0.178	-0.203	0.047	0.128
Q$_t$	-0.134	0.059	-0.039	-0.070	-0.116	0.130	1.000	-0.165	0.052	-0.085	0.049	-0.011	-0.090
LEVERAGE$_t$	-0.088	-0.169	-0.027	-0.043	0.335	0.014	-0.174	1.000	0.283	0.357	-0.442	0.097	0.173
LN_K_L$_t$	-0.228	-0.236	-0.131	0.005	0.381	0.120	-0.010	0.240	1.000	0.250	-0.296	0.001	0.330
LN_AGE$_t$	-0.289	-0.384	-0.105	-0.103	0.606	0.214	-0.142	0.278	0.243	1.000	-0.563	0.050	0.424
NASDAQ$_t$	0.372	0.450	0.147	0.127	-0.639	-0.241	0.115	-0.364	-0.298	-0.567	1.000	-0.089	-0.356
RDMISS$_{t+1}$	-0.035	-0.072	-0.020	-0.025	0.086	0.054	-0.021	0.086	0.029	0.053	-0.089	1.000	-0.153
LN_RDCAP$_t$	-0.337	-0.250	-0.176	0.031	0.675	0.150	-0.097	0.103	0.318	0.429	-0.357	-0.191	1.000

A2. Patent Sample

	AMBIGUITY$_t$	RISK$_t$	ILLIQUIDITY$_t$	GAINPROB$_t$	LN_SALES$_t$	ROA$_t$	Q$_t$	LEVERAGE$_t$	LN_K_L$_t$	LN_AGE$_t$	NASDAQ$_t$	RDMISS$_{t+1}$	LN_RDCAP$_t$
AMBIGUITY$_t$	1.000	-0.033	0.444	-0.050	-0.256	-0.156	-0.167	-0.038	-0.104	-0.087	0.171	-0.026	-0.170
RISK$_t$	0.315	1.000	0.465	0.268	-0.611	-0.315	-0.021	-0.297	-0.222	-0.538	0.584	-0.219	-0.092
ILLIQUIDITY$_t$	0.474	0.246	1.000	-0.001	-0.834	-0.351	-0.291	-0.187	-0.345	-0.493	0.523	-0.060	-0.447
GAINPROB$_t$	0.036	0.282	0.026	1.000	-0.049	-0.152	-0.117	-0.033	0.037	-0.074	0.107	-0.060	0.057
LN_SALES$_t$	-0.469	-0.503	-0.272	-0.041	1.000	0.279	-0.011	0.415	0.288	0.630	-0.653	0.189	0.338
ROA$_t$	-0.371	-0.418	-0.182	-0.168	0.448	1.000	0.448	-0.099	0.026	0.117	-0.147	0.056	0.037
Q$_t$	-0.114	0.071	-0.050	-0.068	-0.100	0.157	1.000	-0.197	0.057	-0.105	0.065	-0.013	-0.031
LEVERAGE$_t$	-0.079	-0.166	-0.015	-0.011	0.327	-0.011	-0.204	1.000	0.244	0.344	-0.412	0.208	-0.027
LN_K_L$_t$	-0.157	-0.172	-0.102	0.038	0.280	0.062	0.004	0.219	1.000	0.183	-0.226	0.008	0.200
LN_AGE$_t$	-0.262	-0.391	-0.131	-0.073	0.593	0.194	-0.164	0.267	0.160	1.000	-0.586	0.142	0.229
NASDAQ$_t$	0.358	0.455	0.185	0.101	-0.627	-0.224	0.136	-0.343	-0.230	-0.576	1.000	-0.210	-0.106
RDMISS$_{t+1}$	-0.092	-0.177	-0.047	-0.063	0.187	0.101	-0.050	0.180	0.052	0.152	-0.210	1.000	-0.615
LN_RDCAP$_t$	-0.127	-0.025	-0.087	0.076	0.266	0.017	-0.001	-0.072	0.128	0.165	-0.060	-0.684	1.000

Table 2: Correlations

B. Correlations Across Size Subsamples

B1. R&D Sample

	Large				Small			
	AMBIGUITY$_t$	RISK$_t$	ILLIQUIDITY$_t$	LN_SALES$_t$	AMBIGUITY$_t$	RISK$_t$	ILLIQUIDITY$_t$	LN_SALES$_t$
AMBIGUITY$_t$	1.000	-0.575	-0.105	0.306	1.000	0.136	0.879	-0.462
RISK$_t$	-0.124	1.000	0.137	-0.355	0.173	1.000	0.201	-0.307
ILLIQUIDITY$_t$	0.485	0.190	1.000	-0.713	0.341	0.159	1.000	-0.505
LN_SALES$_t$	0.178	-0.262	-0.166	1.000	-0.431	-0.260	-0.209	1.000

B2. Patent Sample

	Large				Small			
	AMBIGUITY$_t$	RISK$_t$	ILLIQUIDITY$_t$	LN_SALES$_t$	AMBIGUITY$_t$	RISK$_t$	ILLIQUIDITY$_t$	LN_SALES$_t$
AMBIGUITY$_t$	1.000	-0.583	-0.268	0.373	1.000	0.126	0.873	-0.484
RISK$_t$	-0.227	1.000	0.052	-0.237	0.252	1.000	0.242	-0.462
ILLIQUIDITY$_t$	0.405	0.189	1.000	-0.712	0.447	0.200	1.000	-0.557
LN_SALES$_t$	0.326	-0.187	-0.188	1.000	-0.505	-0.382	-0.244	1.000

Table 3: Determinants of R&D Investment

The table presents OLS regression coefficients for R&D investment. The sample period is 1994-2002. The *Full Sample* consists of all firms with at least two years of data for all variables of interest. The *R&D Sample* consists of all firms with at least two years of data for all variables of interest and at least one year of positive R&D expenditures in Compustat during the sample period. All regressions include firm (*new gvkey*) fixed effects and year fixed effects. Standard errors are clustered by firm. Sample construction is explained in detail in Section 3.1. For variable definitions see Appendix C. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

	$\boldsymbol{RD\_SALES}_{t+1}$		$\boldsymbol{RD\_ASSETS}_{t+1}$	
	Full Sample	R&D Sample	Full Sample	R&D Sample
	(1)	(2)	(3)	(4)
AMBIGUITY_t	-0.053***	-0.089***	-0.009	-0.011
	(0.019)	(0.029)	(0.007)	(0.011)
RISK_t	0.003	-0.024	0.022	0.039
	(0.124)	(0.180)	(0.044)	(0.069)
ILLIQUIDITY_t	-0.005	-0.005	-0.000	-0.000
	(0.004)	(0.005)	(0.001)	(0.001)
LN_SALES_t	-0.020***	-0.036***	-0.006***	-0.009**
	(0.008)	(0.013)	(0.002)	(0.004)
ROA_t	-0.073***	-0.101***	-0.027***	-0.030**
	(0.028)	(0.037)	(0.010)	(0.013)
Q_t	0.002	0.005	-0.002*	-0.002
	(0.003)	(0.004)	(0.001)	(0.001)
LEVERAGE_t	-0.006	-0.017	-0.009	-0.013
	(0.024)	(0.039)	(0.007)	(0.011)
LN_K_L_t	0.004	0.009	0.000	-0.001
	(0.009)	(0.016)	(0.002)	(0.004)
LN_AGE_t	0.022*	0.039*	0.014***	0.022***
	(0.013)	(0.022)	(0.004)	(0.007)
NASDAQ_t	-0.000	-0.004	0.001	0.002
	(0.006)	(0.011)	(0.002)	(0.004)
RDMISS_{t+1}	-0.017***	-0.023***	-0.020***	-0.029***
	(0.005)	(0.007)	(0.004)	(0.005)
LN_RDCAP_t	0.008	0.004	0.000	-0.002
	(0.005)	(0.007)	(0.002)	(0.003)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	14641	7880	14641	7880
Adj. R-squared	0.916	0.892	0.878	0.833

Table 4: Subsample Analysis of R&D Investment

The table presents OLS regression coefficients for R&D investment for all firms with at least two years of data for all variables of interest and at least one year of positive R&D expenditures in Compustat during the sample period (*R&D Sample*). The dependent variable is $\mathrm{RD\_SALES_{t+1}}$. Large (small) firms are firms with sales above (below) the sample median. Unconstrained (constrained) firms are those with KZINDEX below (above) the sample median. Mature (young) firms are those with Compustat age greater than (less than or equal to) 11 years. Low (High) Prob firms are those with GAINPROB below (above) the sample median. The sample period is 1994-2002. All regressions control for $\mathrm{ILLIQUIDITY_t}$, $\mathrm{LN\_SALES_t}$, $\mathrm{ROA_t}$, $\mathrm{Q_t}$, $\mathrm{LEVERAGE_t}$, $\mathrm{LN\_K\_L_t}$, $\mathrm{NASDAQ_t}$, $\mathrm{RDMISS_t}$, $\mathrm{LN\_RDCAP_t}$, as well as firm (*new gvkey*) fixed effects and year fixed effects. Standard errors are clustered by firm. Sample construction is explained in detail in Section 3.1. For variable definitions see Appendix C. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

	Large	Small	NYSE/AMEX	Nasdaq	Unconstrained	Constrained	Mature	Young	Low Prob	High Prob
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathrm{AMBIGUITY}_t$	-0.013	-0.111***	0.002	-0.104***	-0.104*	-0.045	-0.008	-0.124***	-0.014	-0.123**
	(0.013)	(0.035)	(0.034)	(0.033)	(0.056)	(0.035)	(0.029)	(0.042)	(0.028)	(0.060)
RISK_t	0.337***	-0.164	0.099	-0.110	0.001	0.119	-0.011	-0.034	0.054	-0.098
	(0.089)	(0.225)	(0.206)	(0.219)	(0.344)	(0.180)	(0.202)	(0.264)	(0.291)	(0.300)
N	3940	3940	3565	4315	3940	3940	4003	3877	3865	4015

Table 5: Subsample Analysis of R&D Investment: Robustness

The table replicates the analysis in Table 4, excluding from the sample firm-years with sales less than \$20m (Panel 1), firm-years with stock price below \$5 at the end of the previous year (Panel 2), and firms with less than 5 years in Compustat (Panel 3). The dependent variable is RD_SALES_{t+1}. All regressions control for $ILLIQUIDITY_t$, LN_SALES_t, ROA_t, Q_t, $LEVERAGE_t$, $LN\_K\_L_t$, $NASDAQ_t$, $RDMISS_t$, LN_RDCAP_t, as well as firm (*new gvkey*) fixed effects and year fixed effects. Standard errors are clustered by firm. For other robustness tests for R&D investment, see Table IA3. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

	Large	Small	NYSE/AMEX	Nasdaq	Unconstrained	Constrained	Mature	Young	Low Prob	High Prob
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Excluding firm-years with sales less than \$20m										
$AMBIGUITY_t$	-0.013	-0.050*	-0.030*	-0.042	-0.015	-0.041**	-0.031*	-0.044	-0.021	-0.048
	(0.013)	(0.027)	(0.017)	(0.026)	(0.033)	(0.018)	(0.016)	(0.034)	(0.026)	(0.053)
$RISK_t$	0.337***	-0.011	0.170*	0.039	0.433	0.131	-0.153	0.207	0.229	-0.022
	(0.089)	(0.164)	(0.102)	(0.158)	(0.305)	(0.108)	(0.193)	(0.170)	(0.217)	(0.190)
N	3940	3465	3525	3880	3681	3724	3914	3491	3701	3704
2. Excluding firm-years with stock price below \$5 at the end of the previous year										
$AMBIGUITY_t$	-0.008	-0.118**	-0.034	-0.090*	-0.114	0.024	0.015	-0.086	-0.021	-0.020
	(0.016)	(0.055)	(0.028)	(0.049)	(0.074)	(0.050)	(0.038)	(0.069)	(0.035)	(0.097)
$RISK_t$	0.628***	-0.167	0.532**	-0.086	0.066	0.321	0.268	0.032	0.008	-0.025
	(0.125)	(0.313)	(0.217)	(0.297)	(0.456)	(0.313)	(0.335)	(0.347)	(0.388)	(0.488)
N	3839	3051	3399	3491	3557	3333	3686	3204	3582	3308
3. Excluding firms with less than 5 years in Compustat										
$AMBIGUITY_t$	-0.008	-0.083**	-0.001	-0.069*	-0.062	-0.054**	-0.008	-0.097	0.003	-0.100
	(0.016)	(0.041)	(0.035)	(0.038)	(0.078)	(0.026)	(0.029)	(0.063)	(0.034)	(0.065)
$RISK_t$	0.349***	-0.225	0.083	-0.104	0.039	0.116	-0.011	-0.009	0.017	-0.073
	(0.100)	(0.227)	(0.235)	(0.206)	(0.419)	(0.184)	(0.202)	(0.279)	(0.447)	(0.263)
N	3653	2753	3306	3100	3061	3345	4003	2403	3246	3160

Table 6: Determinants of Patenting Activity

The table presents estimation results for count models for patenting activity. In columns (1)-(6), the dependent variable is PATENTS and the sample consists of all firms with at least two years in the presample period, two years of data for all variables of interest and at least one patent application filed during the sample period (the *Patent Sample*). In columns (7)-(12), the dependent variable is CITATIONS and the sample consists of all firms with at least two years in the presample period, two years of data for all variables of interest and at least one *cited* patent applied for during the sample period (the *Citation Sample*). Panel 1 reports estimated coefficients and Panel 2 reports marginal effects, i.e. predicted counts at low (10th percentile of the estimation sample) and high (90th percentile of the estimation sample) $\mathrm{AMBIGUITY_t}$ and $\mathrm{RISK_t}$, while keeping all other variables at their sample means. The sample period is $1994-2002$. All regressions include three-digit SIC code fixed effects, Blundell et al. (1999) presample firm fixed effects, and year fixed effects. Standard errors are clustered by firm. Sample construction is explained in detail in Section 3.1. For variable definitions see Appendix C. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

1. Coefficients

	PATENTS						***CITATIONS***					
	Poisson			Negative Binomial			Poisson			Negative Binomial		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AMBIGUITY$_t$	-1.581***	-2.022***	-2.326***	-0.418*	-0.697**	-1.155***	-1.182**	-1.581**	-1.748**	-0.064	-0.227	-0.700**
	(0.509)	(0.589)	(0.722)	(0.252)	(0.284)	(0.314)	(0.560)	(0.719)	(0.835)	(0.298)	(0.300)	(0.325)
RISK$_t$	2.911	3.420	8.042**	-2.088*	-1.724	0.461	4.904**	5.275**	8.917**	-0.085	1.350	2.715
	(1.938)	(2.241)	(3.660)	(1.067)	(1.269)	(1.810)	(2.072)	(2.510)	(3.646)	(1.523)	(1.821)	(2.488)
ILLIQUIDITY$_t$	0.010	0.022	0.017	-0.005	-0.014	0.003	0.027	-0.018	0.030	0.115	-0.051	0.028
	(0.059)	(0.043)	(0.042)	(0.048)	(0.045)	(0.013)	(0.035)	(0.078)	(0.030)	(0.087)	(0.102)	(0.029)
LN_SALES$_t$	0.328***	0.336***	0.344***	0.307***	0.307***	0.311***	0.453***	0.447***	0.400***	0.354***	0.360***	0.358***
	(0.068)	(0.072)	(0.082)	(0.044)	(0.046)	(0.049)	(0.079)	(0.087)	(0.095)	(0.045)	(0.046)	(0.050)
ROA$_t$	0.044	0.605	1.180**	-0.577***	-0.367	-0.308	0.188	0.896	1.763**	-0.390	-0.193	-0.210
	(0.461)	(0.532)	(0.590)	(0.214)	(0.240)	(0.298)	(0.526)	(0.637)	(0.719)	(0.259)	(0.284)	(0.354)
Q$_t$	0.062*	0.067*	0.063	0.134***	0.162***	0.173***	0.085**	0.096**	0.111**	0.168***	0.196***	0.223***
	(0.033)	(0.037)	(0.045)	(0.027)	(0.031)	(0.038)	(0.040)	(0.043)	(0.047)	(0.036)	(0.039)	(0.047)
LEVERAGE$_t$	-0.493	-0.427	-0.467	-0.450*	-0.510**	-0.727***	-0.694**	-0.643*	-0.525	-0.712***	-0.875***	-1.098***
	(0.300)	(0.312)	(0.345)	(0.237)	(0.253)	(0.279)	(0.316)	(0.356)	(0.407)	(0.227)	(0.240)	(0.280)
LN_K_L$_t$	0.418***	0.455***	0.476***	0.301***	0.307***	0.312***	0.413***	0.408***	0.394***	0.196***	0.211***	0.172**
	(0.130)	(0.131)	(0.130)	(0.049)	(0.052)	(0.060)	(0.104)	(0.106)	(0.109)	(0.057)	(0.062)	(0.068)
LN_AGE$_t$	-0.238***	-0.251***	-0.272***	-0.146***	-0.189***	-0.245***	-0.257***	-0.313***	-0.357***	-0.274***	-0.302***	-0.326***
	(0.080)	(0.079)	(0.099)	(0.054)	(0.061)	(0.072)	(0.086)	(0.098)	(0.120)	(0.064)	(0.075)	(0.085)
NASDAQ$_t$	-0.071	-0.025	-0.024	0.197**	0.181*	0.146	-0.008	-0.077	-0.188	0.026	-0.001	-0.061
	(0.161)	(0.169)	(0.187)	(0.097)	(0.102)	(0.116)	(0.161)	(0.178)	(0.190)	(0.101)	(0.109)	(0.121)
LN_RDCAP$_t$	0.233***	0.235***	0.240***	0.203***	0.212***	0.231***	0.184*	0.214**	0.276***	0.233***	0.245***	0.285***
	(0.070)	(0.075)	(0.079)	(0.033)	(0.034)	(0.036)	(0.094)	(0.098)	(0.094)	(0.034)	(0.035)	(0.038)
N	7416	6334	5148	7416	6334	5148	7050	6041	4935	7050	6041	4935
Pseudo R-squared				0.188	0.181	0.175				0.078	0.079	0.080

2. Marginal effects

(1) Low AMBIGUITY$_t$	6.029	6.123	5.922	5.284	5.410	5.349	63.407	56.072	45.941	64.682	55.865	48.535
(2) High AMBIGUITY$_t$	4.056	3.702	3.376	4.759	4.549	4.046	47.511	38.147	30.340	63.674	52.857	41.100
Marginal Effect (1)-(2)	-1.973***	-2.421***	-2.546***	-0.525*	-0.861**	-1.303***	-15.896**	-17.925**	-15.601**	-1.007	-3.008	-7.435**
	(0.600)	(0.651)	(0.714)	(0.313)	(0.345)	(0.352)	(7.265)	(7.746)	(6.896)	(4.656)	(3.948)	(3.389)
(3) Low RISK$_t$	4.977	4.837	4.292	5.331	5.281	4.833	52.103	44.483	34.457	64.455	53.425	43.865
(4) High RISK$_t$	5.780	5.705	5.948	4.789	4.860	4.924	66.489	56.932	49.370	64.182	56.908	48.941
Marginal Effect (3)-(4)	0.803	0.868	1.656**	-0.542*	-0.421	0.091	14.386**	12.449**	14.913**	-0.273	3.483	5.076
	(0.537)	(0.570)	(0.757)	(0.277)	(0.310)	(0.359)	(6.212)	(6.109)	(6.472)	(4.869)	(4.729)	(4.706)

Table 7: Subsample Analysis of Patenting Activity

The table presents estimation results for count models for patenting activity. When the dependent variable is PATENTS, the sample consists of all firms with at least two years in the presample period, two years of data for all variables of interest and at least one patent application filed during the sample period (the *Patent Sample*). When the dependent variable is CITATIONS, the sample consists of all firms with at least two years in the presample period, two years of data for all variables of interest and at least one *cited* patent applied for during the sample period (the *Citation Sample*). Panel 1 reports estimated coefficients and Panel 2 reports marginal effects, i.e. predicted counts at low (10th percentile of the estimation sample) and high (90th percentile of the estimation sample) AMBIGUITY_t and RISK_t, while keeping all other variables at their sample means. Large (small) firms are firms with sales above (below) the sample median. The sample period is 1994 – 2002. All regressions control for ILLIQUIDITY_t, LN_SALES_t, ROA_t, Q_t, LEVERAGE_t, LN_K_L_t, NASDAQ_t, RDMISS_t, LN_RDCAP_t, as well as three-digit SIC code fixed effects, Blundell et al. (1999) presample firm fixed effects, and year fixed effects. Standard errors are clustered by firm. Sample construction is explained in detail in Section 3.1. For variable definitions see Appendix C. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

1. Coefficients

	Poisson						Negative Binomial					
	Large			Small			Large			Small		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PATENTS												
AMBIGUITY_t	-0.849	-1.446	-1.284	-0.653*	-1.077**	-1.344***	-0.915	-0.790	-0.467	-0.283	-0.572**	-1.081***
	(1.136)	(1.220)	(1.331)	(0.363)	(0.440)	(0.506)	(0.913)	(1.013)	(1.159)	(0.244)	(0.273)	(0.316)
RISK_t	5.514**	6.456**	16.700***	-2.984	-1.745	0.937	3.565	4.755	11.340*	-1.897*	-1.593	-0.570
	(2.379)	(2.828)	(5.399)	(1.841)	(2.237)	(2.428)	(3.288)	(3.937)	(6.087)	(1.051)	(1.231)	(1.659)
N	3708	3185	2634	3708	3149	2514	3708	3185	2634	3708	3149	2514
CITATIONS												
AMBIGUITY_t	-1.299	-1.247	-0.895	-0.408	-0.751**	-1.032**	-2.011*	-1.223	-0.509	-0.260	-0.492	-1.119***
	(1.340)	(1.562)	(1.788)	(0.365)	(0.383)	(0.412)	(1.218)	(1.213)	(1.363)	(0.328)	(0.311)	(0.404)
RISK_t	7.070**	8.123**	13.845**	1.531	2.704	5.413*	2.980	8.041*	17.357**	-0.037	0.032	0.156
	(3.161)	(3.910)	(6.499)	(1.810)	(2.262)	(2.784)	(3.530)	(4.740)	(7.464)	(1.643)	(1.814)	(2.608)
N	3525	3032	2513	3525	3009	2422	3525	3032	2513	3525	3009	2422

2. Marginal effects

PATENTS												
(1) Low AMBIGUITY_t	10.366	9.662	8.418	2.484	2.503	2.437	9.757	8.621	7.149	2.330	2.270	2.219
(2) High AMBIGUITY_t	9.751	8.676	7.640	1.917	1.634	1.454	9.134	8.129	6.901	2.082	1.810	1.465
Marginal Effect (1)-(2)	-0.615	-0.986	-0.778	-0.567*	-0.869**	-0.983	-0.623	-0.492	-0.248	-0.248	-0.460**	-0.754
	(0.821)	(0.829)	(0.803)	(0.312)	(0.356)	N/A	(0.618)	(0.628)	(0.613)	(0.210)	(0.216)	(2216.784)
(3) Low RISK_t	9.499	8.636	7.061	2.467	2.265	2.002	9.113	8.009	6.430	2.361	2.190	1.949
(4) High RISK_t	11.045	10.135	9.956	2.051	2.043	2.095	10.046	9.011	8.119	2.099	1.993	1.896
Marginal Effect (3)-(4)	1.545**	1.499**	2.895***	-0.416	-0.222	0.093	0.933	1.002	1.690*	-0.262*	-0.197	-0.053
	(0.684)	(0.679)	(0.987)	(0.259)	(0.287)	N/A	(0.871)	(0.843)	(0.932)	(0.145)	(0.153)	(156.447)
CITATIONS												
(1) Low AMBIGUITY_t	100.080	82.034	60.134	30.733	25.169	20.346	103.637	82.559	57.542	32.886	26.416	21.684
(2) High AMBIGUITY_t	91.061	74.648	56.147	26.161	18.713	13.698	89.540	75.262	55.342	29.675	21.756	14.117
Marginal Effect (1)-(2)	-9.020	-7.386	-3.987	-4.572	-6.456**	-6.647	-14.097*	-7.297	-2.200	-3.211	-4.661	-7.567
	(9.380)	(9.281)	(7.924)	(4.016)	(3.167)	(11245.080)	(8.479)	(7.166)	(5.877)	(3.975)	(2.891)	N/A
(3) Low RISK_t	88.878	72.596	52.303	27.997	21.325	15.860	94.015	73.179	49.317	31.816	24.744	18.704
(4) High RISK_t	107.845	88.763	69.276	30.689	24.908	20.549	102.002	89.293	70.145	31.746	24.790	18.844
Marginal Effect (3)-(4)	18.967**	16.167**	16.972**	2.692	3.584	4.690	7.987	16.114*	20.828**	-0.070	0.046	0.140
	(8.620)	(8.081)	(8.475)	(3.230)	(3.024)	(7933.024)	(9.556)	(9.764)	(9.403)	(3.130)	(2.581)	N/A

Table 8: Subsample Analysis of Patenting Activity: Robustness

The table replicates the analysis in Table 7, excluding from the sample firm-years in the top 5% of the patent distribution (Panel 1) and firm-years with sales less than \$20m (Panel 2). All regressions control for ILLIQUIDITY_t, LN_SALES_t, ROA_t, Q_t, LEVERAGE_t, LN_K_L_t, NASDAQ_t, RDMISS_t, LN_RDCAP_t, as well as three-digit SIC code fixed effects, Blundell et al. (1999) presample firm fixed effects, and year fixed effects. Standard errors are clustered by firm. Standard errors are clustered by firm. For other robustness tests for patenting activity, see Table IA4. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

1. Excluding firm-years in the top 5% of the patent distribution

	Poisson						Negative Binomial					
	Large			Small			Large			Small		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PATENTS												
AMBIGUITY_t	-0.331	-2.062	-3.720**	-0.601**	-0.993***	-1.277***	-1.005	-0.796	-0.495	-0.259	-0.549**	-1.060***
	(1.283)	(1.528)	(1.723)	(0.304)	(0.383)	(0.455)	(0.981)	(1.107)	(1.357)	(0.236)	(0.268)	(0.311)
RISK_t	3.492	3.527	7.526	-2.485	-1.270	1.496	3.033	4.375	8.100	-1.777*	-1.466	-0.401
	(2.232)	(2.931)	(5.743)	(1.526)	(1.975)	(2.230)	(3.358)	(4.021)	(6.487)	(1.028)	(1.210)	(1.648)
N	3337	2858	2354	3705	3146	2511	3337	2858	2354	3705	3146	2511
CITATIONS												
AMBIGUITY_t	-0.033	-1.230	-2.422	-0.490	-0.677*	-1.270***	-2.627*	-2.014	-0.896	-0.244	-0.439	-1.106***
	(1.563)	(1.650)	(1.867)	(0.378)	(0.383)	(0.414)	(1.414)	(1.428)	(1.682)	(0.325)	(0.307)	(0.392)
RISK_t	7.163**	8.623**	10.956	0.529	0.483	3.306	4.158	9.254*	14.292*	-0.155	-0.043	-0.083
	(2.784)	(4.191)	(7.916)	(1.727)	(2.139)	(2.596)	(3.889)	(4.966)	(8.380)	(1.620)	(1.813)	(2.562)
N	3190	2715	2223	3507	2991	2405	3190	2715	2223	3507	2991	2405

2. Excluding firm-years with sales less than \$20m

PATENTS												
AMBIGUITY_t	-0.849	-1.446	-1.284	-1.052**	-1.452**	-1.535**	-0.915	-0.790	-0.467	-0.608**	-0.876***	-1.235***
	(1.136)	(1.220)	(1.331)	(0.471)	(0.579)	(0.653)	(0.913)	(1.013)	(1.159)	(0.279)	(0.300)	(0.347)
RISK_t	5.514**	6.456**	16.700***	-2.386	-0.862	0.500	3.565	4.755	11.340*	-1.284	-0.951	-1.709
	(2.379)	(2.828)	(5.399)	(2.196)	(2.606)	(2.929)	(3.288)	(3.937)	(6.087)	(1.251)	(1.470)	(1.963)
N	3708	3185	2634	3415	2906	2330	3708	3185	2634	3415	2906	2330
CITATIONS												
AMBIGUITY_t	-1.299	-1.247	-0.895	-0.680*	-0.973**	-1.102**	-2.011*	-1.223	-0.509	-0.580	-0.740**	-1.280***
	(1.340)	(1.562)	(1.788)	(0.408)	(0.417)	(0.456)	(1.218)	(1.213)	(1.363)	(0.359)	(0.349)	(0.427)
RISK_t	7.070**	8.123**	13.845**	2.394	4.084*	5.842*	2.980	8.041*	17.357**	0.913	0.399	-0.506
	(3.161)	(3.910)	(6.499)	(1.938)	(2.354)	(3.034)	(3.530)	(4.740)	(7.464)	(1.943)	(2.029)	(2.797)
N	3525	3032	2513	3264	2790	2252	3525	3032	2513	3264	2790	2252

Table 9: Determinants of Patenting Activity Accounting for Excess Zeroes

The table presents estimation results for count models for patenting activity. In Panel A, the dependent variable is PATENTS and the sample consists of all firms with at least two years in the presample period, two years of data for all variables of interest and at least one patent application filed during the sample period (the *Patent Sample*). In Panel B, the dependent variable is CITATIONS the sample consists of all firms with at least two years in the presample period, two years of data for all variables of interest and at least one *cited* patent applied for during the sample period (the *Citation Sample*). In Panel C, large (small) firms are firms with sales above (below) the sample median. Subpanel 1 reports estimated coefficients and subpanel 2 reports marginal effects, i.e. predicted counts at low (10th percentile of the estimation sample) and high (90th percentile of the estimation sample) $\mathrm{AMBIGUITY_t}$ and $\mathrm{RISK_t}$, while keeping all other variables at their sample means. The sample period is 1994 − 2002. All regressions include Moskowitz and Grinblatt (1999) industry fixed effects, Blundell et al. (1999) presample firm fixed effects, and year fixed effects. Standard errors are clustered by firm. Sample construction is explained in detail in Section 3.1. For variable definitions see Appendix C. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

A. *PATENTS* - All Firms

1. Coefficients

	Negative Binomial			Hurdle Negative Binomial					
				Logit			Zero-Trunc. Neg. Bin.		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathrm{AMBIGUITY}_t$	-0.547**	-0.813***	-1.304***	-0.672**	-0.553	-0.564	-0.564*	-0.903**	-1.606***
	(0.253)	(0.289)	(0.322)	(0.312)	(0.352)	(0.431)	(0.319)	(0.354)	(0.369)
RISK_t	-0.483	0.058	2.648	-1.793	-0.710	-0.799	-0.040	0.504	3.880*
	(1.210)	(1.444)	(2.031)	(1.748)	(1.954)	(2.728)	(1.356)	(1.627)	(2.226)
$\mathrm{ILLIQUIDITY}_t$	-0.015	-0.026	-0.001	-0.038	-0.032	0.014	-0.011	-0.062	-0.011
	(0.047)	(0.042)	(0.015)	(0.040)	(0.045)	(0.046)	(0.077)	(0.065)	(0.017)
$\mathrm{LN\_SALES}_t$	0.292***	0.292***	0.289***	0.031	0.051	0.042	0.355***	0.350***	0.350***
	(0.044)	(0.045)	(0.046)	(0.043)	(0.045)	(0.051)	(0.045)	(0.046)	(0.046)
ROA_t	-0.574**	-0.403	-0.313	0.059	0.476*	0.585*	-0.727**	-0.683**	-0.656
	(0.238)	(0.270)	(0.333)	(0.247)	(0.273)	(0.329)	(0.286)	(0.333)	(0.417)
Q_t	0.144***	0.172***	0.181***	0.066*	0.073**	0.074*	0.151***	0.184***	0.194***
	(0.028)	(0.032)	(0.038)	(0.035)	(0.036)	(0.040)	(0.030)	(0.035)	(0.042)
$\mathrm{LEVERAGE}_t$	-0.402	-0.433	-0.633*	-0.350	-0.417	-0.583	-0.368	-0.404	-0.635**
	(0.270)	(0.286)	(0.324)	(0.311)	(0.344)	(0.384)	(0.286)	(0.292)	(0.322)
$\mathrm{LN\_K\_L}_t$	0.269***	0.282***	0.273***	0.182***	0.206***	0.217***	0.290***	0.292***	0.273***
	(0.056)	(0.057)	(0.059)	(0.054)	(0.059)	(0.067)	(0.063)	(0.064)	(0.065)
$\mathrm{LN\_AGE}_t$	-0.207***	-0.248***	-0.296***	-0.120*	-0.084	-0.037	-0.227***	-0.282***	-0.350***
	(0.062)	(0.068)	(0.076)	(0.062)	(0.067)	(0.078)	(0.066)	(0.073)	(0.083)
NASDAQ_t	0.251**	0.248**	0.185	0.117	0.139	0.101	0.257**	0.239**	0.179
	(0.112)	(0.116)	(0.117)	(0.115)	(0.122)	(0.137)	(0.117)	(0.122)	(0.125)
$\mathrm{LN\_RDCAP}_t$	0.219***	0.232***	0.254***	0.160***	0.151***	0.165***	0.215***	0.230***	0.249***
	(0.029)	(0.029)	(0.029)	(0.025)	(0.028)	(0.031)	(0.031)	(0.031)	(0.031)
N	7416	6334	5148				7416	6334	5148
Pseudo R-squared	0.172	0.164	0.158						

2. Marginal effects

(1) Low $\mathrm{AMBIGUITY}_t$	6.065	6.613	7.322	1.908	1.746	1.646	1.875	1.971	2.097
(2) High $\mathrm{AMBIGUITY}_t$	5.288	5.402	5.343	1.739	1.608	1.510	1.733	1.747	1.709
Marginal Effect (1)-(2)	-0.777**	-1.211***	-1.980***	-0.169**	-0.138	-0.136	-0.141*	-0.225**	-0.388***
	(0.357)	(0.428)	(0.494)	(0.078)	(0.088)	(0.104)	(0.080)	(0.088)	(0.089)
(3) Low RISK_t	5.855	6.173	6.304	1.889	1.714	1.614	1.829	1.886	1.902
(4) High RISK_t	5.711	6.190	7.019	1.797	1.680	1.581	1.827	1.911	2.060
Marginal Effect (3)-(4)	-0.144	0.017	0.715	-0.092	-0.034	-0.032	-0.002	0.024	0.157*
	(0.358)	(0.431)	(0.559)	(0.090)	(0.094)	(0.111)	(0.070)	(0.078)	(0.090)

Table 9: Determinants of Patenting Activity Accounting for Excess Zeroes

B. *CITATIONS* - All Firms

1. Coefficients

	Negative Binomial			Hurdle Negative Binomial					
				Logit			Zero-Trunc. Neg. Bin.		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AMBIGUITY_t	-0.187	-0.276	-0.831**	-0.436	-0.422	-0.729*	0.077	0.045	-0.337
	(0.303)	(0.287)	(0.324)	(0.329)	(0.367)	(0.443)	(0.257)	(0.257)	(0.283)
RISK_t	2.510	4.540**	7.762***	-2.361	-2.492	-1.751	4.920***	6.854***	11.274***
	(1.706)	(2.031)	(2.938)	(1.861)	(2.047)	(2.819)	(1.580)	(1.874)	(2.828)
ILLIQUIDITY_t	0.067	-0.108*	0.021	-0.040	-0.027	0.026	0.090	-0.102*	0.012
	(0.088)	(0.057)	(0.028)	(0.042)	(0.049)	(0.049)	(0.065)	(0.055)	(0.018)
LN_SALES_t	0.366***	0.369***	0.364***	0.122***	0.143***	0.140***	0.403***	0.403***	0.405***
	(0.044)	(0.044)	(0.046)	(0.042)	(0.045)	(0.052)	(0.037)	(0.038)	(0.038)
ROA_t	-0.276	-0.146	-0.087	0.036	0.325	0.556	-0.378	-0.287	-0.186
	(0.285)	(0.300)	(0.360)	(0.272)	(0.303)	(0.365)	(0.247)	(0.266)	(0.308)
Q_t	0.194***	0.228***	0.242***	0.088**	0.124***	0.125***	0.178***	0.198***	0.215***
	(0.038)	(0.039)	(0.046)	(0.037)	(0.037)	(0.043)	(0.034)	(0.038)	(0.043)
LEVERAGE_t	-0.610**	-0.681**	-0.909***	-0.153	-0.210	-0.585	-0.645***	-0.737***	-0.863***
	(0.273)	(0.287)	(0.329)	(0.306)	(0.342)	(0.381)	(0.222)	(0.230)	(0.268)
LN_K_L_t	0.222***	0.241***	0.219***	0.130**	0.172***	0.175**	0.228***	0.233***	0.206***
	(0.064)	(0.065)	(0.067)	(0.055)	(0.061)	(0.068)	(0.059)	(0.061)	(0.063)
LN_AGE_t	-0.391***	-0.386***	-0.379***	-0.131**	-0.089	-0.053	-0.332***	-0.358***	-0.379***
	(0.074)	(0.082)	(0.091)	(0.061)	(0.068)	(0.078)	(0.065)	(0.075)	(0.085)
NASDAQ_t	0.169	0.123	0.009	0.011	0.066	0.011	0.154	0.092	-0.010
	(0.116)	(0.126)	(0.138)	(0.114)	(0.125)	(0.137)	(0.109)	(0.120)	(0.131)
LN_RDCAP_t	0.233***	0.246***	0.274***	0.179***	0.182***	0.201***	0.191***	0.200***	0.218***
	(0.029)	(0.030)	(0.035)	(0.025)	(0.027)	(0.031)	(0.027)	(0.029)	(0.034)
N	7050	6041	4935				7050	6041	4935
Pseudo R-squared	0.070	0.069	0.070						

2. Marginal effects

(1) Low AMBIGUITY_t	77.487	75.512	75.559	1.321	1.195	1.117	4.714	4.709	4.726
(2) High AMBIGUITY_t	74.023	70.597	62.036	1.214	1.092	0.944	4.733	4.720	4.646
Marginal Effect (1)-(2)	-3.464	-4.915	-13.523***	-0.106	-0.103	-0.173*	0.019	0.011	-0.080
	(5.577)	(5.085)	(5.236)	(0.080)	(0.089)	(0.105)	(0.063)	(0.063)	(0.067)
(3) Low RISK_t	72.512	67.641	62.193	1.333	1.208	1.087	4.620	4.581	4.513
(4) High RISK_t	82.148	83.643	85.055	1.216	1.091	1.016	4.865	4.901	4.968
Marginal Effect (3)-(4)	9.636	16.002**	22.861**	-0.117	-0.117	-0.071	0.245***	0.321***	0.455***
	(6.697)	(7.499)	(9.348)	(0.093)	(0.096)	(0.114)	(0.079)	(0.088)	(0.114)

Table 9: Determinants of Patenting Activity Accounting for Excess Zeroes

C. Large vs Small Firms

Coefficients

	Large						Small					
	Logit			Zero-Trunc. Neg. Bin.			Logit			Zero-Trunc. Neg. Bin.		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PATENTS												
AMBIGUITY_t	-3.539**	-2.609	0.312	-0.199	-0.522	-0.791	-0.472	-0.448	-0.722	-0.434	-0.811**	-1.347***
	(1.631)	(2.084)	(2.534)	(0.998)	(1.030)	(1.208)	(0.345)	(0.384)	(0.469)	(0.308)	(0.342)	(0.378)
RISK_t	-3.450	6.139	3.460	11.991***	11.141***	20.051***	-2.583	-1.190	-1.209	-0.831	0.086	2.094
	(4.728)	(6.130)	(8.333)	(3.629)	(4.051)	(6.169)	(1.934)	(2.067)	(2.890)	(1.228)	(1.561)	(1.967)
N				3708	3185	2634				3708	3149	2514
CITATIONS												
AMBIGUITY_t	-2.508	-3.151	-2.396	0.646	0.443	-0.001	-0.474	-0.673*	-1.183***	-0.381	-0.329	-0.628*
	(1.834)	(2.035)	(2.379)	(1.284)	(1.130)	(1.088)	(0.345)	(0.380)	(0.458)	(0.279)	(0.261)	(0.335)
RISK_t	-3.166	-4.145	-5.019	15.738***	18.223***	33.405***	-3.023	-2.507	-1.705	2.145	3.496**	4.045*
	(4.992)	(6.663)	(9.533)	(3.940)	(4.525)	(7.133)	(1.986)	(2.095)	(2.867)	(1.380)	(1.612)	(2.197)
N				3525	3032	2513				3525	3009	2422

Table IA1: Descriptive Statistics

The table presents descriptive statistics for the variables used in the analysis. The sample period is 1994-2002. The *Full Sample* (Panel A) consists of all firms with at least two years of data for all variables of interest. The *Patent Sample* (Panel B) consists of all firms with at least two years in the presample period, two years of data for all variables of interest and at least one patent application filed during the sample period. For each sample, descriptive statistics are presented for all firms (e.g. Panel A1), for large firms (e.g. Panel A2) and for small firms (e.g. Panel A3). Large (small) firms are those with sales above (below) the sample median for NYSE/AMEX/NASDAQ firms in year t. Sample construction is explained in detail in Section 3.1. For variable definitions see Appendix C.

A1: Full Sample - All Firms

Variable	N	Mean	St. Dev.	Min	10th Pct.	25th Pct.	Median	75th Pct.	90th Pct.	Max
AMBIGUITY$_t$	14,641	0.116	0.156	0.007	0.015	0.025	0.049	0.131	0.336	0.844
RISK$_t$	14,641	0.029	0.030	0.001	0.005	0.010	0.020	0.037	0.063	0.253
ILLIQUIDITY$_t$	14,641	0.203	0.893	0.000	0.001	0.005	0.027	0.137	0.460	51.319
GAINPROB$_t$	14,641	0.501	0.030	0.282	0.465	0.482	0.500	0.520	0.539	0.667
SALES$_t$	14,641	2,834.891	10,434.110	0.077	43.648	139.523	547.863	1,807.411	5,632.456	234,484.600
ASSETS$_t$	14,641	2,728.383	13,052.050	3.142	53.658	135.635	475.355	1,628.062	5,128.105	386,814.800
MCAP$_t$	14,641	3,402.740	13,031.770	3.715	75.149	174.681	540.820	1,735.892	5,942.436	310,071.700
RDCAP$_t$	14,641	353.413	2,243.975	0.000	0.000	0.000	14.655	108.145	434.276	60,235.960
ROA$_t$	14,641	0.113	0.178	-1.841	-0.049	0.081	0.141	0.199	0.262	0.445
Q$_t$	14,641	1.545	1.230	0.146	0.673	0.887	1.202	1.756	2.733	20.000
LEVERAGE$_t$	14,641	0.214	0.199	0.000	0.000	0.032	0.184	0.333	0.472	1.000
KZINDEX$_t$	14,641	-4.601	23.421	-1,150.516	-11.012	-3.970	-0.702	0.898	1.936	87.204
K_L$_t$	14,641	91.488	229.397	0.044	9.923	16.822	30.549	63.685	156.912	1,535.646
AGE$_t$	14,641	17.504	14.893	1.000	3.000	5.000	11.000	29.000	44.000	51.000
NASDAQ$_t$	14,641	0.516	0.500	0.000	0.000	0.000	1.000	1.000	1.000	1.000
RDMISS$_{t+1}$	14,641	0.331	0.471	0.000	0.000	0.000	0.000	1.000	1.000	1.000
RD_SALES$_{t+1}$	14,641	0.102	0.397	0.000	0.000	0.000	0.007	0.079	0.199	5.093
RD_ASSETS$_{t+1}$	14,641	0.056	0.098	0.000	0.000	0.000	0.007	0.075	0.172	0.625
PATENTS$_{t+1}$	14,641	16.140	87.288	0.000	0.000	0.000	0.000	3.000	21.000	2,579.000
CITATIONS$_{t+1}$	14,641	219.475	1,406.037	0.000	0.000	0.000	0.000	30.251	252.342	61,310.880

Table IA1: Descriptive Statistics

A2: Full Sample - Large Firms

Variable	N	Mean	St. Dev.	Min	10th Pct.	25th Pct.	Median	75th Pct.	90th Pct.	Max
$AMBIGUITY_t$	7,320	0.055	0.067	0.007	0.016	0.023	0.037	0.059	0.099	0.834
$RISK_t$	7,320	0.017	0.018	0.001	0.004	0.006	0.011	0.022	0.037	0.249
$ILLIQUIDITY_t$	7,320	0.038	0.043	0.000	0.000	0.001	0.005	0.022	0.073	5.071
$GAINPROB_t$	7,320	0.500	0.028	0.282	0.466	0.482	0.498	0.517	0.534	0.630
$SALES_t$	7,320	5,483.594	14,272.890	548.076	683.724	947.239	1,807.897	4,407.736	12,349.200	234,484.600
$ASSETS_t$	7,320	5,233.582	18,114.180	105.758	474.583	778.201	1,600.887	3,891.629	10,888.530	386,814.800
$MCAP_t$	7,320	6,414.532	17,920.970	5.310	294.312	644.856	1,564.606	4,440.134	12,805.450	310,071.700
$RDCAP_t$	7,320	659.168	3,143.083	0.000	0.000	0.000	5.044	278.728	1,122.207	60,235.960
ROA_t	7,320	0.159	0.079	-0.693	0.075	0.112	0.153	0.201	0.254	0.445
Q_t	7,320	1.409	0.970	0.286	0.723	0.902	1.152	1.582	2.286	20.000
$LEVERAGE_t$	7,320	0.264	0.183	0.000	0.025	0.132	0.251	0.366	0.491	1.000
$KZINDEX_t$	7,320	-2.414	13.366	-450.604	-6.601	-2.789	-0.389	0.976	1.866	43.301
K_L_t	7,320	91.176	199.558	0.120	11.720	19.988	35.689	75.229	185.951	1,535.646
AGE_t	7,320	24.826	15.933	1.000	5.000	9.000	25.000	39.000	47.000	51.000
$NASDAQ_t$	7,320	0.250	0.433	0.000	0.000	0.000	0.000	0.000	1.000	1.000
$RDMISS_{t+1}$	7,320	0.373	0.484	0.000	0.000	0.000	0.000	1.000	1.000	1.000
RD_SALES_{t+1}	7,320	0.024	0.053	0.000	0.000	0.000	0.000	0.022	0.073	1.561
RD_ASSETS_{t+1}	7,320	0.022	0.043	0.000	0.000	0.000	0.000	0.025	0.072	0.605
$PATENTS_{t+1}$	7,320	30.098	121.640	0.000	0.000	0.000	0.000	9.000	62.000	2,579.000
$CITATIONS_{t+1}$	7,320	402.107	1,965.646	0.000	0.000	0.000	0.000	84.876	645.607	61,310.880

Table IA1: Descriptive Statistics

A3: Full Sample - Small Firms

Variable	N	Mean	St. Dev.	Min	10th Pct.	25th Pct.	Median	75th Pct.	90th Pct.	Max
$AMBIGUITY_t$	7,321	0.178	0.191	0.007	0.015	0.032	0.098	0.268	0.467	0.844
$RISK_t$	7,321	0.041	0.035	0.002	0.011	0.018	0.031	0.051	0.082	0.253
$ILLIQUIDITY_t$	7,321	0.368	1.231	0.000	0.013	0.033	0.109	0.328	0.828	51.319
$GAINPROB_t$	7,321	0.503	0.032	0.284	0.463	0.482	0.502	0.524	0.543	0.667
$SALES_t$	7,321	186.550	152.832	0.077	22.343	56.355	139.523	298.891	432.917	547.863
$ASSETS_t$	7,321	223.527	286.321	3.142	32.766	64.943	136.024	285.067	476.453	5,832.165
$MCAP_t$	7,321	391.360	629.430	3.715	48.928	93.970	198.702	463.542	905.253	14,077.650
$RDCAP_t$	7,321	47.699	79.166	0.000	0.000	0.000	17.128	63.563	130.535	1,007.480
ROA_t	7,321	0.068	0.230	-1.841	-0.202	0.013	0.120	0.196	0.269	0.445
Q_t	7,321	1.681	1.430	0.146	0.620	0.865	1.273	1.966	3.146	20.000
$LEVERAGE_t$	7,321	0.163	0.201	0.000	0.000	0.002	0.079	0.267	0.446	1.000
$KZINDEX_t$	7,321	-6.787	30.148	-1,150.516	-16.857	-5.835	-1.171	0.812	2.020	87.204
K_L_t	7,321	91.801	255.788	0.044	8.629	14.669	26.012	52.407	127.426	1,535.646
AGE_t	7,321	10.183	9.087	1.000	3.000	4.000	7.000	13.000	24.000	51.000
$NASDAQ_t$	7,321	0.782	0.413	0.000	0.000	1.000	1.000	1.000	1.000	1.000
$RDMISS_{t+1}$	7,321	0.289	0.453	0.000	0.000	0.000	0.000	1.000	1.000	1.000
RD_SALES_{t+1}	7,321	0.181	0.548	0.000	0.000	0.000	0.043	0.150	0.322	5.093
RD_ASSETS_{t+1}	7,321	0.090	0.122	0.000	0.000	0.000	0.041	0.136	0.245	0.625
$PATENTS_{t+1}$	7,321	2.184	7.378	0.000	0.000	0.000	0.000	1.000	6.000	269.000
$CITATIONS_{t+1}$	7,321	36.868	154.721	0.000	0.000	0.000	0.000	11.074	85.735	5,089.890

Table IA1: Descriptive Statistics

B1: Citation Sample - All Firms

Variable	N	Mean	St. Dev.	Min	10th Pct.	25th Pct.	Median	75th Pct.	90th Pct.	Max
AMBIGUITY_t	7,050	0.097	0.134	0.007	0.015	0.025	0.046	0.095	0.259	0.840
RISK_t	7,050	0.025	0.025	0.001	0.004	0.008	0.016	0.032	0.054	0.249
ILLIQUIDITY_t	7,050	0.135	0.644	0.000	0.001	0.002	0.014	0.080	0.298	39.813
GAINPROB_t	7,050	0.500	0.029	0.284	0.465	0.482	0.499	0.518	0.537	0.630
SALES_t	7,050	3,973.708	13,742.050	0.495	52.163	191.413	792.843	2,707.756	8,694.496	234,484.600
ASSETS_t	7,050	4,145.112	18,007.750	3.142	64.989	180.378	700.066	2,606.975	8,454.530	386,814.800
MCAP_t	7,050	5,314.379	16,938.650	4.814	99.572	250.386	858.817	3,185.322	10,550.590	310,071.700
RDCAP_t	7,050	688.696	3,187.990	0.000	0.000	14.749	77.289	289.137	1,092.910	60,235.960
ROA_t	7,050	0.125	0.163	-1.687	-0.021	0.093	0.150	0.204	0.263	0.445
Q_t	7,050	1.539	1.169	0.158	0.690	0.904	1.207	1.754	2.674	20.000
LEVERAGE_t	7,050	0.196	0.175	0.000	0.000	0.035	0.176	0.304	0.416	1.000
KZINDEX_t	7,050	-3.934	13.600	-328.112	-9.859	-4.296	-1.243	0.454	1.467	72.427
K_L_t	7,050	68.580	123.915	1.685	13.644	22.133	36.003	68.875	136.981	1,535.646
AGE_t	7,050	21.781	15.966	2.000	4.000	7.000	16.000	36.000	46.000	51.000
NASDAQ_t	7,050	0.445	0.497	0.000	0.000	0.000	0.000	1.000	1.000	1.000
RDMISS_{t+1}	7,050	0.190	0.392	0.000	0.000	0.000	0.000	0.000	1.000	1.000
RD_SALES_{t+1}	7,050	0.127	0.419	0.000	0.000	0.005	0.034	0.114	0.213	5.093
RD_ASSETS_{t+1}	7,050	0.072	0.097	0.000	0.000	0.005	0.035	0.104	0.184	0.625
PATENTS_{t+1}	7,050	32.780	123.238	0.000	0.000	1.000	3.000	14.000	65.000	2,579.000
CITATIONS_{t+1}	7,050	445.614	1,997.201	0.000	0.000	0.000	27.567	170.687	736.986	61,310.880
EXPLOIT_{t+1}	5,291	0.274	0.290	0.000	0.000	0.000	0.212	0.450	0.667	1.000
EXPLORE_{t+1}	5,291	0.609	0.329	0.000	0.100	0.368	0.619	1.000	1.000	1.000

Table IA1: Descriptive Statistics

B2: Citation Sample - Large Firms

Variable	N	Mean	St. Dev.	Min	10th Pct.	25th Pct.	Median	75th Pct.	90th Pct.	Max
AMBIGUITY$_t$	3,525	0.050	0.041	0.007	0.017	0.025	0.040	0.060	0.090	0.562
RISK$_t$	3,525	0.014	0.015	0.001	0.003	0.005	0.009	0.017	0.031	0.194
ILLIQUIDITY$_t$	3,525	0.012	0.043	0.000	0.000	0.001	0.002	0.008	0.023	1.176
GAINPROB$_t$	3,525	0.500	0.027	0.407	0.468	0.483	0.498	0.516	0.534	0.630
SALES$_t$	3,525	7,687.022	18,711.120	792.952	996.204	1,438.278	2,707.756	6,691.361	16,623.720	234,484.600
ASSETS$_t$	3,525	8,019.982	24,870.430	217.935	802.326	1,262.328	2,606.646	6,659.452	16,755.250	386,814.800
MCAP$_t$	3,525	10,085.660	22,961.760	13.364	594.331	1,226.285	3,057.617	7,539.678	23,484.300	310,071.700
RDCAP$_t$	3,525	1,293.383	4,425.473	0.000	0.000	10.500	209.264	794.137	2,423.342	60,235.960
ROA$_t$	3,525	0.165	0.076	-0.231	0.084	0.119	0.160	0.206	0.258	0.445
Q$_t$	3,525	1.459	0.943	0.286	0.783	0.945	1.197	1.647	2.345	12.358
LEVERAGE$_t$	3,525	0.248	0.156	0.000	0.042	0.139	0.241	0.338	0.440	1.000
KZINDEX$_t$	3,525	-2.215	6.495	-194.423	-6.681	-3.418	-0.933	0.520	1.463	14.006
K_L$_t$	3,525	89.454	154.325	1.685	18.544	27.048	45.088	91.046	187.558	1,535.646
AGE$_t$	3,525	30.765	15.492	2.000	7.000	15.000	34.000	45.000	48.000	51.000
NASDAQ$_t$	3,525	0.157	0.363	0.000	0.000	0.000	0.000	0.000	1.000	1.000
RDMISS$_{t+1}$	3,525	0.250	0.433	0.000	0.000	0.000	0.000	0.000	1.000	1.000
RD_SALES$_{t+1}$	3,525	0.037	0.057	0.000	0.000	0.000	0.016	0.046	0.113	0.453
RD_ASSETS$_{t+1}$	3,525	0.034	0.047	0.000	0.000	0.000	0.017	0.047	0.101	0.318
PATENTS$_{t+1}$	3,525	60.435	169.443	0.000	0.000	1.000	8.000	44.000	138.000	2,579.000
CITATIONS$_{t+1}$	3,525	802.194	2,767.316	0.000	0.000	1.926	62.145	392.976	1,735.944	61,310.880
EXPLOIT$_{t+1}$	2,799	0.279	0.247	0.000	0.000	0.045	0.250	0.429	0.587	1.000
EXPLORE$_{t+1}$	2,799	0.591	0.286	0.000	0.231	0.388	0.583	0.809	1.000	1.000

Table IA1: Descriptive Statistics

B3: Citation Sample - Small Firms

Variable	N	Mean	St. Dev.	Min	10th Pct.	25th Pct.	Median	75th Pct.	90th Pct.	Max
$AMBIGUITY_t$	3,525	0.144	0.173	0.007	0.013	0.024	0.063	0.204	0.408	0.840
$RISK_t$	3,525	0.035	0.029	0.001	0.009	0.016	0.027	0.045	0.069	0.249
$ILLIQUIDITY_t$	3,525	0.258	0.892	0.000	0.008	0.021	0.070	0.223	0.591	39.813
$GAINPROB_t$	3,525	0.500	0.031	0.284	0.463	0.481	0.500	0.522	0.539	0.616
$SALES_t$	3,525	260.394	223.962	0.495	26.235	67.837	191.413	418.742	625.519	792.734
$ASSETS_t$	3,525	270.242	272.919	3.142	39.808	79.325	180.378	389.985	590.542	2,850.809
$MCAP_t$	3,525	543.098	1,063.629	4.814	64.270	125.875	270.602	609.722	1,148.529	28,795.460
$RDCAP_t$	3,525	84.009	114.612	0.000	0.000	15.779	45.477	106.867	211.400	1,050.844
ROA_t	3,525	0.086	0.210	-1.687	-0.162	0.036	0.133	0.202	0.268	0.445
Q_t	3,525	1.619	1.354	0.158	0.614	0.847	1.227	1.891	2.993	20.000
$LEVERAGE_t$	3,525	0.143	0.177	0.000	0.000	0.002	0.071	0.238	0.384	1.000
$KZINDEX_t$	3,525	-5.652	17.941	-328.112	-13.571	-5.442	-1.585	0.347	1.471	72.427
K_L_t	3,525	47.705	77.630	1.771	11.226	17.934	29.477	51.594	94.126	1,535.646
AGE_t	3,525	12.797	10.413	2.000	3.000	5.000	9.000	16.000	30.000	51.000
$NASDAQ_t$	3,525	0.733	0.443	0.000	0.000	0.000	1.000	1.000	1.000	1.000
$RDMISS_{t+1}$	3,525	0.130	0.336	0.000	0.000	0.000	0.000	0.000	1.000	1.000
RD_SALES_{t+1}	3,525	0.216	0.576	0.000	0.000	0.020	0.082	0.168	0.343	5.093
RD_ASSETS_{t+1}	3,525	0.109	0.118	0.000	0.000	0.022	0.078	0.153	0.246	0.625
$PATENTS_{t+1}$	3,525	5.126	11.765	0.000	0.000	0.000	2.000	5.000	12.000	269.000
$CITATIONS_{t+1}$	3,525	89.034	257.581	0.000	0.000	0.000	14.701	73.610	220.132	5,089.890
$EXPLOIT_{t+1}$	2,492	0.269	0.331	0.000	0.000	0.000	0.125	0.500	0.857	1.000
$EXPLORE_{t+1}$	2,492	0.628	0.370	0.000	0.000	0.333	0.671	1.000	1.000	1.000

Table IA2: Correlations

The table presents correlation coefficients for the variables used in the analysis. The *Full Sample* consists of all firms with at least two years of data for all variables of interest. The *Citation Sample* consists of all firms with at least two years in the presample period, two years of data for all variables of interest and at least one *cited* patent applied for during the sample period. Panel A reports correlations for all firms in the *Full Sample* (A1) and the *Citation Sample* (A2). Panel B reports selected correlations for large and small firms in each sample separately. The sample period is 1994-2002. Entries below the diagonal are Pearson correlations, and entries above the diagonal are Spearman correlations. Sample construction is explained in detail in Section 3.1. For variable definitions see Appendix C.

A. Correlations for All Firms

A1. Full Sample

	$AMBIGUITY_t$	$RISK_t$	$ILLIQUIDITY_t$	$GAINPROB_t$	LN_SALES_t	ROA_t	Q_t	$LEVERAGE_t$	$LN\_K\_L_t$	LN_AGE_t	$NASDAQ_t$	$RDMISS_{t+1}$	LN_RDCAP_t
$AMBIGUITY_t$	1.000	0.094	0.619	-0.031	-0.385	-0.189	-0.177	-0.055	-0.140	-0.156	0.257	-0.030	-0.072
$RISK_t$	0.316	1.000	0.481	0.283	-0.580	-0.341	-0.048	-0.227	-0.216	-0.498	0.543	-0.159	-0.023
$ILLIQUIDITY_t$	0.424	0.234	1.000	0.030	-0.770	-0.339	-0.273	-0.126	-0.297	-0.438	0.520	-0.002	-0.255
$GAINPROB_t$	0.031	0.307	0.042	1.000	-0.075	-0.171	-0.136	-0.023	0.013	-0.103	0.110	-0.047	0.041
LN_SALES_t	-0.475	-0.467	-0.247	-0.064	1.000	0.286	-0.068	0.362	0.183	0.553	-0.594	0.117	0.085
ROA_t	-0.334	-0.427	-0.155	-0.181	0.435	1.000	0.415	-0.082	0.039	0.126	-0.143	0.065	-0.023
Q_t	-0.116	0.041	-0.052	-0.075	-0.133	0.147	1.000	-0.190	0.066	-0.117	0.060	0.020	-0.025
$LEVERAGE_t$	-0.053	-0.120	-0.015	0.001	0.273	-0.006	-0.186	1.000	0.269	0.229	-0.348	0.230	-0.165
$LN\_K\_L_t$	-0.150	-0.152	-0.090	0.016	0.138	0.052	-0.010	0.260	1.000	0.182	-0.229	0.075	0.158
LN_AGE_t	-0.251	-0.363	-0.105	-0.099	0.538	0.163	-0.153	0.158	0.142	1.000	-0.521	0.071	0.185
$NASDAQ_t$	0.372	0.409	0.164	0.107	-0.567	-0.192	0.112	-0.290	-0.226	-0.522	1.000	-0.148	-0.037
$RDMISS_{t+1}$	-0.066	-0.135	-0.025	-0.047	0.119	0.120	-0.020	0.219	0.151	0.077	-0.148	1.000	-0.628
LN_RDCAP_t	-0.074	0.013	-0.054	0.051	0.128	-0.063	-0.003	-0.168	0.066	0.183	-0.051	-0.628	1.000

A2. Citation Sample

	$AMBIGUITY_t$	$RISK_t$	$ILLIQUIDITY_t$	$GAINPROB_t$	LN_SALES_t	ROA_t	Q_t	$LEVERAGE_t$	$LN\_K\_L_t$	LN_AGE_t	$NASDAQ_t$	$RDMISS_{t+1}$	LN_RDCAP_t
$AMBIGUITY_t$	1.000	-0.052	0.429	-0.059	-0.242	-0.147	-0.166	-0.028	-0.102	-0.079	0.155	-0.014	-0.180
$RISK_t$	0.311	1.000	0.456	0.266	-0.606	-0.307	-0.020	-0.298	-0.224	-0.534	0.587	-0.216	-0.099
$ILLIQUIDITY_t$	0.463	0.245	1.000	-0.010	-0.835	-0.344	-0.295	-0.186	-0.350	-0.490	0.519	-0.054	-0.470
$GAINPROB_t$	0.026	0.279	0.022	1.000	-0.040	-0.149	-0.118	-0.030	0.046	-0.067	0.103	-0.060	0.058
LN_SALES_t	-0.460	-0.496	-0.263	-0.031	1.000	0.269	-0.008	0.417	0.293	0.631	-0.649	0.178	0.371
ROA_t	-0.370	-0.405	-0.177	-0.162	0.441	1.000	0.452	-0.101	0.028	0.110	-0.141	0.041	0.044
Q_t	-0.117	0.073	-0.050	-0.068	-0.094	0.171	1.000	-0.191	0.063	-0.107	0.058	-0.010	-0.034
$LEVERAGE_t$	-0.072	-0.162	-0.013	-0.009	0.331	-0.001	-0.204	1.000	0.240	0.350	-0.412	0.207	-0.012
$LN\_K\_L_t$	-0.160	-0.171	-0.101	0.046	0.284	0.060	0.007	0.216	1.000	0.181	-0.234	0.026	0.200
LN_AGE_t	-0.259	-0.391	-0.126	-0.066	0.594	0.187	-0.162	0.275	0.159	1.000	-0.591	0.138	0.241
$NASDAQ_t$	0.349	0.458	0.177	0.097	-0.623	-0.218	0.128	-0.345	-0.240	-0.581	1.000	-0.200	-0.127
$RDMISS_{t+1}$	-0.081	-0.175	-0.041	-0.064	0.176	0.089	-0.048	0.181	0.075	0.148	-0.200	1.000	-0.610
LN_RDCAP_t	-0.141	-0.032	-0.091	0.078	0.292	0.029	0.001	-0.061	0.117	0.172	-0.078	-0.688	1.000

Table IA2: Correlations

B. Correlations Across Size Subsamples

B1. Full Sample

	Large				Small			
	AMBIGUITY$_t$	RISK$_t$	ILLIQUIDITY$_t$	LN_SALES$_t$	AMBIGUITY$_t$	RISK$_t$	ILLIQUIDITY$_t$	LN_SALES$_t$
AMBIGUITY$_t$	1.000	-0.437	0.001	0.182	1.000	0.158	0.879	-0.448
RISK$_t$	0.084	1.000	0.220	-0.280	0.210	1.000	0.242	-0.392
ILLIQUIDITY$_t$	0.601	0.277	1.000	-0.658	0.389	0.184	1.000	-0.490
LN_SALES$_t$	0.038	-0.217	-0.177	1.000	-0.428	-0.320	-0.211	1.000

B2. Citation Sample

	Large				Small			
	AMBIGUITY$_t$	RISK$_t$	ILLIQUIDITY$_t$	LN_SALES$_t$	AMBIGUITY$_t$	RISK$_t$	ILLIQUIDITY$_t$	LN_SALES$_t$
AMBIGUITY$_t$	1.000	-0.596	-0.280	0.388	1.000	0.118	0.872	-0.483
RISK$_t$	-0.252	1.000	0.043	-0.236	0.259	1.000	0.236	-0.455
ILLIQUIDITY$_t$	0.406	0.156	1.000	-0.712	0.438	0.207	1.000	-0.560
LN_SALES$_t$	0.343	-0.187	-0.219	1.000	-0.504	-0.370	-0.237	1.000

Table IA3: Subsample Analysis of R&D Investment: Robustness

The table replicates the analysis in Table 4, excluding from the sample firm-years in the top 5% of the patent distribution (Panel 1) and controlling for the probability of gain, GAINPROB (Panel 2). For other robustness tests for R&D investment, see Table 5. The dependent variable is $\mathrm{RD\_SALES_{t+1}}$. All regressions control for $\mathrm{ILLIQUIDITY_t}$, $\mathrm{LN\_SALES_t}$, $\mathrm{ROA_t}$, $\mathrm{Q_t}$, $\mathrm{LEVERAGE_t}$, $\mathrm{LN\_K\_L_t}$, $\mathrm{NASDAQ_t}$, $\mathrm{RDMISS_t}$, $\mathrm{LN\_RDCAP_t}$, as well as firm (*new gvkey*) fixed effects and year fixed effects. Standard errors are clustered by firm. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

	Large	Small	NYSE/AMEX	Nasdaq	Unconstrained	Constrained	Mature	Young	Low Prob	High Prob
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Excluding firm-years in the top 5% of the patent distribution										
$\mathrm{AMBIGUITY}_t$	-0.001	-0.112***	0.007	-0.108***	-0.109*	-0.050	-0.011	-0.127***	-0.014	-0.132**
	(0.010)	(0.035)	(0.037)	(0.033)	(0.059)	(0.035)	(0.030)	(0.043)	(0.029)	(0.062)
RISK_t	0.224***	-0.166	0.004	-0.114	-0.014	0.106	-0.059	-0.044	0.037	-0.127
	(0.082)	(0.225)	(0.232)	(0.221)	(0.354)	(0.187)	(0.218)	(0.266)	(0.299)	(0.312)
N	3227	3931	2963	4195	3561	3597	3388	3770	3524	3634
2. Controlling for the Probability of Gain, GAINPROB										
$\mathrm{AMBIGUITY}_t$	-0.011	-0.111***	0.003	-0.104***	-0.104*	-0.046	-0.008	-0.123***	-0.015	-0.124**
	(0.014)	(0.034)	(0.034)	(0.032)	(0.056)	(0.034)	(0.029)	(0.042)	(0.028)	(0.060)
RISK_t	0.311***	-0.168	0.086	-0.126	-0.058	0.131	-0.018	-0.048	0.057	-0.112
	(0.089)	(0.232)	(0.203)	(0.229)	(0.345)	(0.185)	(0.205)	(0.270)	(0.295)	(0.311)
$\mathrm{GAINPROB}_t$	0.047	0.028	0.034	0.080	0.273*	-0.045	0.021	0.080	-0.030	0.137
	(0.031)	(0.159)	(0.037)	(0.140)	(0.158)	(0.068)	(0.050)	(0.157)	(0.123)	(0.231)
N	3940	3940	3565	4315	3940	3940	4003	3877	3865	4015

Table IA4: Subsample Analysis of Patenting Activity: Robustness

The table replicates the analysis in Table 7, excluding from the sample firm-years with stock price below $5 at the end of the previous year (Panel 1) and firms with less than 5 years in Compustat (Panel 2), and controlling for the probability of gain, GAINPROB (Panel 5). All regressions control for ILLIQUIDITY$_t$, LN_SALES$_t$, ROA$_t$, Q$_t$, LEVERAGE$_t$, LN_K_L$_t$, NASDAQ$_t$, RDMISS$_t$, LN_RDCAP$_t$, as well as firm (*new gvkey*) fixed effects and year fixed effects. Standard errors are clustered by firm. For other robustness tests for patenting activity, see Table 8. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

1. Excluding firm-years with stock price below $5 at the end of the previous year

	Poisson						Negative Binomial					
	Large			Small			Large			Small		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PATENTS												
AMBIGUITY$_t$	-0.687	-1.301	-1.186	-0.728	-1.149**	-1.335**	-0.501	-0.726	-0.279	-0.310	-0.604*	-1.029***
	(1.108)	(1.205)	(1.319)	(0.467)	(0.544)	(0.616)	(1.002)	(1.071)	(1.166)	(0.310)	(0.338)	(0.366)
RISK$_t$	7.740***	7.585**	17.491***	-1.724	-0.627	2.269	7.304*	7.146*	12.967**	-1.066	-0.764	-0.300
	(2.942)	(3.031)	(5.306)	(2.184)	(2.514)	(2.480)	(3.731)	(3.894)	(6.017)	(1.304)	(1.455)	(1.907)
N	3643	3138	2615	3119	2676	2202	3643	3138	2615	3119	2676	2202
CITATIONS												
AMBIGUITY$_t$	-1.196	-1.165	-0.827	-0.332	-0.860*	-0.918*	-1.169	-1.144	-0.662	-0.045	-0.550	-1.325***
	(1.333)	(1.559)	(1.790)	(0.433)	(0.450)	(0.481)	(1.268)	(1.334)	(1.336)	(0.385)	(0.389)	(0.444)
RISK$_t$	8.382**	8.819**	14.321**	3.448*	4.182*	6.822**	8.326**	8.985*	17.658**	-0.023	-1.068	-1.467
	(3.697)	(4.003)	(6.519)	(2.072)	(2.512)	(3.063)	(4.244)	(5.110)	(7.507)	(1.977)	(2.145)	(2.883)
N	3465	2988	2495	2990	2580	2134	3465	2988	2495	2990	2580	2134

2. Excluding firms with less than 5 years in Compustat

PATENTS												
AMBIGUITY$_t$	-0.842	-1.404	-1.316	-1.020**	-1.348**	-1.891***	-0.886	-0.698	-0.341	-0.389	-0.596*	-1.306***
	(1.146)	(1.211)	(1.338)	(0.512)	(0.596)	(0.611)	(0.933)	(1.030)	(1.166)	(0.304)	(0.336)	(0.362)
RISK$_t$	7.415***	8.560***	14.852***	-3.853*	-3.012	-0.310	4.651	6.204	12.974**	-2.699**	-2.639*	-0.862
	(2.323)	(2.968)	(5.167)	(2.081)	(2.423)	(2.620)	(3.512)	(4.057)	(6.148)	(1.174)	(1.384)	(2.060)
N	3545	3036	2511	2969	2470	1943	3545	3036	2511	2969	2470	1943
CITATIONS												
AMBIGUITY$_t$	-1.184	-1.052	-0.815	-0.567	-0.855	-1.445***	-1.856	-0.890	0.007	-0.133	-0.218	-1.480***
	(1.362)	(1.582)	(1.821)	(0.495)	(0.520)	(0.524)	(1.231)	(1.208)	(1.347)	(0.375)	(0.362)	(0.446)
RISK$_t$	8.659***	9.723**	12.255*	-0.718	0.803	3.566	3.687	9.343*	19.467**	-2.564	-1.614	-0.651
	(3.188)	(4.324)	(6.605)	(1.962)	(2.239)	(2.905)	(3.845)	(4.864)	(7.573)	(1.706)	(2.132)	(3.041)
N	3377	2898	2402	2820	2358	1872	3377	2898	2402	2820	2358	1872

Table IA4: Subsample Analysis of Patenting Activity: Robustness

3. Controlling for the Probability of Gain, GAINPROB

	Poisson						Negative Binomial					
	Large			Small			Large			Small		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PATENTS												
$AMBIGUITY_t$	-0.846	-1.407	-1.231	-0.628*	-1.060**	-1.342***	-0.901	-0.794	-0.463	-0.259	-0.538**	-1.074***
	(1.130)	(1.205)	(1.306)	(0.354)	(0.430)	(0.502)	(0.912)	(1.014)	(1.162)	(0.239)	(0.270)	(0.314)
$RISK_t$	5.585**	7.470**	18.050***	-3.972**	-2.854	-0.104	2.799	4.893	12.267**	-2.233**	-1.988	-0.691
	(2.430)	(3.013)	(5.634)	(2.007)	(2.449)	(2.636)	(3.342)	(4.090)	(6.108)	(1.076)	(1.253)	(1.677)
$GAINPROB_t$	-0.102	-1.135	-1.215	3.855***	4.611***	4.351**	1.125	-0.185	-1.088	1.514*	2.456**	0.938
	(0.793)	(1.167)	(1.251)	(1.354)	(1.513)	(1.735)	(0.793)	(0.889)	(0.905)	(0.891)	(0.987)	(1.128)
N	3708	3185	2634	3708	3149	2514	3708	3185	2634	3708	3149	2514
CITATIONS												
$AMBIGUITY_t$	-1.438	-1.315	-0.961	-0.395	-0.735*	-1.021**	-1.952	-1.264	-0.469	-0.239	-0.448	-1.120***
	(1.314)	(1.541)	(1.741)	(0.362)	(0.377)	(0.412)	(1.218)	(1.214)	(1.361)	(0.326)	(0.307)	(0.404)
$RISK_t$	6.051*	7.522*	13.193**	0.640	1.023	4.155	1.835	8.631*	19.013**	-0.327	-0.510	0.203
	(3.188)	(3.927)	(6.263)	(1.856)	(2.287)	(2.773)	(3.651)	(4.988)	(7.503)	(1.632)	(1.804)	(2.607)
$GAINPROB_t$	1.354	0.668	0.602	3.179**	5.443***	3.830*	1.636	-0.892	-1.641	1.187	2.879**	-0.327
	(0.916)	(1.291)	(1.378)	(1.291)	(1.467)	(2.076)	(1.115)	(1.256)	(1.212)	(1.160)	(1.188)	(1.432)
N	3525	3032	2513	3525	3009	2422	3525	3032	2513	3525	3009	2422

Table IA5: Determinants of Innovation Style

The table presents OLS regression coefficients for innovation style. The dependent variables are EXPLOIT, the percentage of patents based on the firm's prior knowledge, and EXPLORE, the percentage of patents based on new knowledge. The sample consists of all firms with at least two years in the presample period, two years of data for all variables of interest and at least one patent application filed during the sample period (the *Patent Sample*). The sample period is 1994-2002. All regressions include firm (*new gvkey*) fixed effects and year fixed effects. Standard errors are clustered by firm. Sample construction is explained in detail in Section 3.1. For variable definitions see Appendix C. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

	EXPLOIT			***EXPLORE***		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
AMBIGUITY_t	-0.151*	-0.090	-0.104	0.150*	0.027	0.301**
	(0.080)	(0.114)	(0.132)	(0.090)	(0.120)	(0.147)
RISK_t	-0.080	0.047	-0.684	-0.321	-0.057	0.839
	(0.361)	(0.429)	(0.631)	(0.432)	(0.440)	(0.643)
ILLIQUIDITY_t	0.001	0.028	0.050	-0.004	-0.011	-0.055
	(0.019)	(0.051)	(0.043)	(0.025)	(0.049)	(0.036)
LN_SALES_t	-0.019	-0.046*	0.012	0.012	0.039	-0.006
	(0.022)	(0.027)	(0.028)	(0.026)	(0.027)	(0.032)
ROA_t	-0.087	0.112	-0.203*	0.102	0.038	0.147
	(0.088)	(0.114)	(0.113)	(0.095)	(0.127)	(0.122)
Q_t	0.004	0.003	-0.006	-0.004	-0.003	0.006
	(0.006)	(0.008)	(0.007)	(0.006)	(0.008)	(0.008)
LEVERAGE_t	-0.056	0.071	-0.136*	0.028	-0.038	0.087
	(0.059)	(0.067)	(0.070)	(0.064)	(0.073)	(0.076)
LN_K_L_t	0.005	0.015	0.019	0.007	-0.002	-0.029
	(0.023)	(0.026)	(0.026)	(0.025)	(0.027)	(0.031)
LN_AGE_t	0.139***	0.144**	0.076	-0.182***	-0.214***	-0.118
	(0.050)	(0.059)	(0.068)	(0.056)	(0.067)	(0.081)
NASDAQ_t	-0.117***	-0.041	-0.123**	0.104*	0.060	0.067
	(0.043)	(0.063)	(0.056)	(0.054)	(0.060)	(0.060)
LN_RDCAP_t	0.033**	0.050**	0.026	-0.026	-0.033	-0.043
	(0.016)	(0.025)	(0.023)	(0.022)	(0.023)	(0.029)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5408	3922	3139	5408	3922	3139
Adj. R-squared	0.375	0.417	0.470	0.414	0.447	0.486