ESSAYS IN FIRM-LEVEL PATENTING ACTIVITY AND FINANCIAL OUTCOMES

by

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To my parents. Thank you for teaching me the joy of learning and instilling in me the importance of education.

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ABSTRACT

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In Chapter 1, I construct a new proxy for Tobin's q that incorporates the replacement cost of patent capital. This proxy, PI (physical plus intangible) q, explains up to 64% more variation in investment than other proxies for q. Furthermore, investment is more sensitive to PI q than to other proxies for q. Although investment is predicted more accurately by, and is more sensitive to, PI q, controlling for PI q leads to relatively higher, not lower, cash flow coefficients. All results are stronger in subsamples with more patent capital. Overall, using PI q strengthens the historically weak investment-q relation.

Chapter 2 includes Noah Stoffman and M. Deniz Yavuz as co-authors, and in this chapter, we find that small innovators (i.e., small, innovative firms) earn higher returns than small non-innovators for up to five years. We find no such innovative premium among large firms. A battery of tests shows that our results are explained by risk, not investor underreaction. Small innovators are especially risky because they focus more on risky product innovation and rely more on organization capital that amplifies their systematic risk. In addition, small innovators contribute significantly to the size premium. Overall, small innovators have a higher cost of equity, which potentially explains why they rely heavily on internal capital.

CHAPTER 1. USING PATENT CAPITAL TO ESTIMATE TOBIN'S Q

1.1 Introduction

Tobin's q, which is the market value of capital divided by the replacement cost of capital, has been called the most commonly-used regressor in studies of empirical corporate finance (Erickson and Whited, 2012). Despite the widespread use of q as a proxy for investment opportunities, empirically, the investment-q relation is surprisingly weak (Erickson and Whited, 2000). One reason for this weak investment-q relation is that since Tobin's q is not perfectly observable, proxies for q likely contain substantial measurement error. Furthermore, in previous proxies for q, estimates of the market value of capital include both physical capital and intangible capital, but estimates of the replacement cost of capital usually include only physical capital.[1] This exclusion of the replacement cost of intangible capital adds to measurement error in q (Erickson and Whited, 2006). In an effort to reduce this measurement error, I construct a new proxy for q that includes patent capital, which has been shown to be important for firm value but whose replacement cost has been excluded from previous proxies for q.

The exclusion of the replacement cost of intangible capital in previous proxies for q is striking, but understandable. Intangible capital is either externally-purchased or internally-created. However, only externally-purchased intangible capital appears on the balance sheet. Thus, internally-created intangible capital, which can be quite large for firms in some industries (e.g., healthcare), is much harder to estimate. One component of internally-created intangible capital that is important for firm value and has experienced significant growth in recent decades is patents. For example, Figure 1.1 shows that the estimated annual market value of patents issued to publicly-traded firms has grown from less than \$300 billion in the early 1990s to over \$3 trillion in recent years (Kogan et al., 2017; Stoffman et al., 2020). In

[1] Recent examples include Alti (2003); Bolton et al. (2011); Chen and Chen (2012); and Erickson and Whited (2012). One notable exception is Peters and Taylor (2017).

previous proxies for q, the market value of these patents has been included in the numerator, but since patents are internally-created, the replacement cost of these patents has been excluded from the denominator. Therefore, I focus on including the replacement cost of patent capital when constructing my proxy for q.

Investments associated with the development of patent capital cannot be recorded on the balance sheet, so I estimate the replacement cost of patent capital as a function of estimated patent values, which are determined by the market response to newly-granted patents (Kogan et al., 2017; Stoffman et al., 2020). Specifically, I estimate the replacement cost of new patents as the market value of new patents divided by the marginal q of new patents. I apply the perpetual inventory method to the replacement cost of new patents to obtain the replacement cost of patent capital.

I then use the replacement cost of patent capital to construct my proxy for q, which I call PI (physical plus intangible) q. The numerator of PI q is the market value of capital. The denominator of PI q, or the replacement cost of total capital, is physical capital plus my estimate of intangible capital, which is the replacement cost of patent capital plus on-balance sheet intangible capital (i.e., externally-purchased intangible capital). Thus, when estimating intangible capital, I include only components that have been valued by either the market or the firm.

Given q's theoretical role as the sole determinant of new investment, I follow an extensive literature dating back to at least Ciccolo (1975) and Abel (1980) and empirically test the q theory of investment by regressing investment on lagged q. I find that PI q explains significantly more variation in firm-level investment than two commonly-used proxies for q. Specifically, PI q explains 21% of the variation in physical investment, 36% of the variation in research and development (R&D) investment, and 42% of the variation in total (physical plus R&D) investment. These percentages are up to 64% (i.e., 14 percentage points) higher than those from regressions of investment on physical q (Erickson and Whited, 2012), whose denominator includes only physical capital, or total q (Peters and Taylor, 2017), whose denominator includes physical capital and an estimate of intangible capital that excludes the replacement cost of patent capital.

Since Tobin's q is not perfectly observable, any proxy for q contains measurement error that results in biased coefficient estimates on q when using ordinary least squares (Erickson and Whited, 2000). To obtain bias-corrected coefficients on q, I use a cumulant estimator (Erickson et al., 2014). This methodology is important because when regressing investment on q, the coefficient on q can be interpreted as a determinant of the elasticity of investment with respect to q (Whited, 1994; Erickson and Whited, 2000), and previous work has found this coefficient to be lower than expected (Philippon, 2009). However, I find that coefficients on q, and thus elasticities of investment with respect to q, are almost always higher when using PI q.

PI q's outperformance is driven in part by the inclusion of the replacement cost of patent capital, so I expect PI q's outperformance to be stronger in subsamples with more patent capital, which is indeed what I find. Specifically, the explanatory power of PI q and coefficients on PI q are relatively larger when focusing on industries and time periods with more patent capital. In these subsamples, PI q is less correlated with, and on average, relatively lower than, physical q and total q. Relatively lower values of PI q are consistent with the implication that many high estimates of q that include only physical capital are due in part to missing patent capital in the denominator of q (Griliches, 1981; Cockburn and Griliches, 1988; Megna and Klock, 1993).

Although q's theoretical role is as the only determinant of new investment, there exists a large literature showing that even after controlling for q, investment is positively associated with cash flow (Hassett and Hubbard, 1997; Caballero, 1999). This positive investment-cash flow relation has been interpreted as evidence of financing constraints (Fazzari et al., 1988; Brown et al., 2009), the result of measurement error in q (Erickson and Whited, 2000; Gomes, 2001), and cash flow providing additional information about future investment opportunities (Gilchrist and Himmelberg, 1995; Alti, 2003). Previous research suggests that controlling for a better proxy for q should result in lower cash flow coefficients (e.g., Kaplan and Zingales, 1997). However, I find that although PI q is a significantly better proxy for q than both physical q and total q, controlling for PI q leads to relatively higher, not lower, cash flow coefficients.

This initially unexpected result may be due to differences in investment-cash flow correlations when controlling for different proxies for q. Investment-cash flow correlations are different when controlling for different proxies for q because q theory implies that when regressing investment on q and cash flow, the denominators of all regression variables should be the same (Hayashi and Inoue, 1991; Erickson and Whited, 2012). Thus, by changing the denominator of q, I am also changing the denominators of both investment and cash flow. As a result, when investment, q, and cash flow are all scaled by the denominator of PI q, investment-cash flow correlations increase relatively more than investment-q correlations. Consequently, controlling for PI q leads to higher, not lower, cash flow coefficients. This finding shows that controlling for a better proxy for q does not necessarily result in lower cash flow coefficients, as previously suggested.

In robustness tests, I show that my main results are (i) insensitive to the depreciation rate used to estimate the replacement cost of patent capital, (ii) insensitive to the marginal q used to estimate the replacement cost of new patents, (iii) robust to alternative econometric specifications, (iv) driven by both the replacement cost of patent capital and on-balance sheet intangible capital, and (v) strongest when intangible capital is estimated using just the replacement cost of patent capital and on-balance sheet intangible capital.

This paper contributes to the vast literature associated with Tobin's q proxy construction (e.g., Tobin and Brainard, 1977; Fazzari et al., 1988; Lewellen and Badrinath, 1997; Erickson and Whited, 2006; Philippon, 2009), but it is most closely related to Peters and Taylor (2017). Peters and Taylor (2017) construct their own proxy for q that also includes an estimate of the replacement cost of intangible capital, which they estimate as on-balance sheet intangible capital plus knowledge capital and organization capital. Knowledge capital and organization capital are estimated by cumulating and depreciating R&D expenses (BEA; Damodaran, 1999) and 30% of selling, general, and administrative (SG&A) expenses (Eisfeldt and Papanikolaou, 2013, 2014).

In contrast, I construct a proxy for q that includes the replacement cost of patent capital. Rather than estimate patent capital by cumulating and depreciating expenses associated with the development of patents, I estimate patent capital as a function of the market response to newly-granted patents. I argue that using the market response is a more direct way to estimate the replacement cost of patent capital. The results herein show that by estimating the replacement cost of intangible capital as a function of its market value, I am able to construct a proxy for q that creates a stronger investment-q relation.

1.2 The q theory of investment

The q theory of investment was developed in the late 1960s (Brainard and Tobin, 1968; Tobin, 1969), but the main idea behind q theory was not incorporated into the neoclassical theory of investment (Jorgenson, 1963), which assumes no adjustment costs, until convex adjustment costs were introduced (Lucas and Prescott, 1971; Mussa, 1977; Abel, 1983). As shown below, with convex adjustment costs, the optimal level of investment for a manager who maximizes firm value is a function of only q.

The following model of investment is from Whited (1994). The relative price of capital goods is normalized to one. Risk-neutral managers in a tax-free environment choose investment each period to maximize firm value V_{it} at time t:

$$V_{it} = E_t\left\{ \sum_{j=0}^{\infty} b^j \left[\Pi(K_{i,t+j}) - I_{i,t+j} - \frac{c_1}{2}\left(\frac{I_{it}}{K_{it}} - c_0 - v_{it} \right)^2 K_{it} \right] \right\}, \tag{1.1}$$

s.t.

$$K_{i,t+1} = (1 - d_{it})K_{it} + I_{it}, \tag{1.2}$$

in which i indexes firms, b is the firm's discount factor, K_{it} is total capital, and I_{it} is investment. $\Pi(K_{it})$ is the profit function; $\Pi_K > 0$, $\Pi_{KK} = 0$, K_{it} is the only quasi-fixed factor, and variable factors have been maximized out.

The last term in (1) is the investment adjustment cost function, which is positive and convex in I_{it} and negative and convex in K_{it}. c_0 and c_1 are constants, and $c_1 > 0$ to ensure concavity of the value function. v_{it} is an exogenous shock, and it is observed by the firm but not the econometrician at time t. In a time-series context, v_{it} represents a technological shock. In a cross-sectional context, v_{it} represents random differences among firms. The presence of this shock is necessary for the derivation of the error term in a linear investment-q regression.

In the constraint (1.2), d_{it} is the rate of capital depreciation for firm i. Let q^*_{it} be the sequence of Lagrange multipliers on the constraint. Maximizing firm value subject to its constraint yields:

$$1 + c_1\left(\frac{I_{it}}{K_{it}} - c_0 - v_{it}\right) = E_t(q^*_{it}) \equiv q_{it}, \tag{1.3}$$

in which

$$q^*_{it} = \sum_{s=1}^{\infty} b^s(1-d_{it})^{s-1}\left[\Pi_K(K_{i,t+s}) - \frac{c_1\big(K_{it}(c_0+v_{it})^2 - {I_{it}}^2\big)}{2{K_{it}}^2}\right]. \tag{1.4}$$

Equation (1.3) states that the firm equates marginal adjustment costs of capital with the expected shadow value of capital, q^*_{it}, which equation (1.4) shows is the present value of marginal net profits from using the capital. The price of capital is one, so q_{it} is marginal q. Rearranging equation (1.3) yields:

$$\frac{I_{it}}{K_{it}} = \alpha + \beta q_{it} + \varepsilon_{it}, \tag{1.5}$$

in which $\alpha \equiv c_0 - \dfrac{1}{c_1}$, $\beta \equiv \dfrac{1}{c_1}$, and $\varepsilon_{it} \equiv v_{it}$. Empirical tests of the q theory of investment are most often tests of equation (1.5) (e.g., Erickson and Whited, 2006; Andrei et al., 2019). I estimate the same regression using my proxy for q.

1.3 Data

The sample includes all annual Compustat firms between fiscal years 1975 and 2017 except financials (SIC codes 6000-6799), utilities (SIC codes 4900-4999), and public administration and nonclassified firms (SIC codes 9000-9999).[2] Following Peters and Taylor (2017),

[2] I use Standard Industry Classification Code (*sic*).

I exclude firms with non-positive total assets; non-positive sales; and gross property, plant, and equipment of less than $5 million (1990 dollars). I also exclude singleton observations and observations with missing values of investment, q, or cash flow. When analyzing R&D investment and total investment, which is physical investment plus R&D investment, I remove firms whose average R&D investment over the entire sample is zero. To mitigate the impact of outliers, I winsorize all regression variables at the 1% and 99% levels.[3]

1.3.1 Proxies for q

Tobin's q is the market value of capital divided by the replacement cost of capital. Previously, estimates of the market value of capital included both physical capital and intangible capital, but estimates of the replacement cost of capital mostly included only physical capital. Excluding the replacement cost of intangible capital results in additional measurement error in q (Erickson and Whited, 2006). Since the importance of intangible capital has been growing in recent decades (Corrado and Hulten, 2010), measurement error in q associated with the exclusion of intangible capital has also been growing.

Most previous proxies for q likely exclude the replacement cost of intangible capital because it is difficult to measure. Firm-level intangible capital is either externally-purchased or internally-created. The book value of externally-purchased intangible capital appears on the balance sheet and includes goodwill and other intangible capital, which includes any separately identifiable intangible asset. On the other hand, investments associated with internally-created intangible capital are immediately expensed on the income statement, so they do not appear on the balance sheet. Thus, the replacement cost of internally-created intangible capital is much harder to estimate.

An important component of internally-created intangible capital is patents. Not only has the estimated annual market value of patents issued to publicly-traded firms grown

[3]In unreported tests, I find that my results are qualitatively similar when winsorizing at the 5% and 95% levels.

significantly in the past few decades (Figure 1.1), but firms with more valuable patents earn higher long-run growth in output, productivity, and profitability (Kogan et al., 2017). Given the importance of patents to firm value and the exclusion of the replacement cost of patent capital in previous proxies for q, I construct PI q, which includes the replacement cost of patent capital:

$$q_{it}^{PI} = \frac{V_{it}}{K_{it}^{phy} + K_{it}^{int^{PI}}}, \tag{1.6}$$

in which V_{it} is the market value of outstanding common equity (*csho* times *prcc_f*) plus the book value of short- and long-term debt (*dlc* plus *dltt*) minus the book value of current assets (*act*). K_{it}^{phy} is physical capital, which is the book value of gross property, plant, and equipment (*ppegt*). I estimate intangible capital as follows:

$$K_{it}^{int^{PI}} = K_{it}^{P} + K_{it}^{on-bs}, \tag{1.7}$$

in which K_{it}^{P} is the replacement cost of patent capital, and K_{it}^{on-bs} is on-balance sheet intangible capital. Thus, when estimating the replacement cost of intangible capital, I include only components that do not require assumptions about how much intangible capital is created through associated expenses. The estimation procedure for patent capital is discussed below, and on-balance sheet intangible capital is from Compustat (*intan*). I set all missing values of the replacement cost of patent capital and on-balance sheet intangible to zero.

I use the perpetual inventory method to estimate the replacement cost of patent capital:

$$K_{it}^{P} = (1 - \delta_P)K_{i,t-1}^{P} + P_{it}, \tag{1.8}$$

in which δ_P is an industry-specific depreciation rate, and P_{it} is the replacement cost of new patents. R&D is closely related to subsequently-issued patents, so beginning with the earliest possible data, I estimate patent capital using depreciation rates for R&D capital from Table 4 of Li (2012).[4,5] I cumulate and depreciate patent capital on a monthly basis.[6] In robustness tests, I find that my results are unaffected by alternative depreciation rates.

I estimate the replacement cost of new patents as the market value of new patents divided by the marginal q of new patents. New patent values are a function of the three-day idiosyncratic return following the announcement of newly-granted patents (Kogan et al., 2017; Stoffman et al., 2020). I assume new patents have a marginal q of 1.5. Lindenberg and Ross (1981) argue that capitalized rents across a number of firms with substantial market power result in an average of q of 1.5 between 1960 and 1977. Additionally, Philippon (2009) constructs a macro-level q whose estimates oscillate around 1.5 between 1953 and 2007. In robustness tests, I find that my results are unaffected by alternative estimates for the marginal q of new patents. In other words, it is the inclusion of the replacement cost of patent capital that is driving my results, not the marginal q of new patents.

In standard investment-q regressions, I compare the performance of PI q to two commonly-used proxies for q. The first proxy is from Erickson and Whited (2012), and I will refer to it as physical q:

$$q_{it}^{phy} = \frac{V_{it}}{K_{it}^{phy}}. \tag{1.9}$$

The denominator of physical q includes only physical capital.

The second proxy is from Peters and Taylor (2017), and it is called total q:

$$q_{it}^{tot} = \frac{V_{it}}{K_{it}^{phy} + K_{it}^{int^{tot}}}. \tag{1.10}$$

[4] The data in this paper begin in 1975, but estimated patent values begin in 1926.

[5] If the industry is not explicitly listed, I follow guidelines set by the Bureau of Economic Analysis (BEA) and use an annual rate of 15%.

[6] For example, if the annual accumulation rate is 0.85 (i.e., depreciation rate of 0.15), I use a monthly accumulation rate of 0.9865, which equals $0.85^{1/12}$.

The denominator of total q includes an estimate of intangible capital that excludes patent capital:

$$K_{it}^{int^{tot}} = K_{it}^{know} + K_{it}^{org} + K_{it}^{on-bs}, \tag{1.11}$$

in which K_{it}^{know} is estimated knowledge capital, and K_{it}^{org} is estimated organization capital. Estimates of both are from Wharton Research Data Services. Using the perpetual inventory method, Peters and Taylor (2017) cumulate and depreciate R&D expenses to estimate knowledge capital and 30% of SG&A expenses to estimate organization capital. Thus, total q relies on assumptions about how much intangible capital is created through associated expenses.

1.3.2 Summary statistics

Table 1.1 presents estimates of different proxies for q and estimates of intangible capital for five different percentiles. Panel A presents estimates of q for all firms. Since not all firms have patent capital, Panel B presents estimates of q for firms with patent capital at any point during the sample. Both panels show that the inclusion of intangible capital in PI q lowers many of the high estimates of physical q.

Panel C presents estimates of intangible capital for all firms, and Panel D presents estimates of intangible capital for firms with patent capital. The first two rows in each panel show that estimates of intangible capital and patent capital are both positively skewed. The last two rows in each panel present estimates of patent intensity and intangible intensity. Patent intensity is patent capital divided by total capital, and intangible intensity is intangible capital divided by total capital. Importantly, Panel D shows that patent capital is often a significant portion of total intangible capital for firms that have patent capital.

Figure 1.2 presents firm-year observation totals and percentages in five Fama-French industries. Panel A shows that in the full sample, firms in high-tech and healthcare comprise about 31% of all observations. However, Panel B shows that when focusing on firms with patent capital, firms in high-tech and healthcare comprise over 41% of the observations. These are the two industries one might expect a higher proportion of firms to have patent capital.

Since R&D investment is not as well populated in Compustat as physical investment (i.e., capital expenditures), Panels C and D of Figure 1.2 present firm-year observation totals and percentages for firms with R&D investment. Panel C shows that firms in the same two industries, high-tech and healthcare, comprise 53% of observations with R&D. A comparison of observation totals in Panels A and C shows that high-tech and healthcare are the only two industries in which more than half of all observations have R&D investment. Panel D shows that of all observations with R&D and patent capital at any point during the sample, 53% of them are in high-tech and healthcare.

Overall, Figure 1.2 shows that there is significant inter-industry variation in the percentage of firms with patent capital. As one might expect, firms in high-tech and healthcare are more likely to have patent capital than firms in other industries. Given this inter-industry variation, I expect the relative performance of PI q to differ across industries, which I test for later by estimating regressions after sorting firms by industry.

1.4 Investment-q relation

In this section, I test the q theory of investment by regressing investment on PI q, physical q, or total q. Since q theory implies that the same divisor be used for all regression variables, all investment variables are scaled by the denominator of lagged q being regressed on by investment (Hayashi and Inoue, 1991; Erickson and Whited, 2012). Using different divisors for investment and q breaks their natural positive correlation, which leads to lower coefficient estimates on q and lower R^2 estimates (Erickson and Whited, 2012).[7] I estimate physical investment as scaled capital expenditures (*capx*), R&D investment as scaled research and development expenses (*xrd*), and total investment as physical investment plus R&D investment.

1.4.1 OLS results

Table 1.2 presents results from ordinary least squares (OLS) regressions of investment on lagged q. Following the investment-q literature, I also include firm fixed effects and year fixed effects. Since q is measured with error, the coefficient on q is biased toward zero when using OLS (Erickson and Whited, 2000). For this reason, the discussion surrounding Table 1.2 focuses on within R^2 estimates, which are ordinary R^2 estimates from estimating OLS on the transformed data. ΔR^2 estimates are R^2 estimates associated with PI q minus R^2 estimates associated with either physical q or total q within each investment type. Measurement error in q is discussed and addressed in the next subsection.

Panel A of Table 1.2 presents results for all firms. The first three columns focus on physical investment, the middle three columns focus on R&D investment, and the last three columns focus on total investment. For all investment types, R^2 estimates associated with PI q are significantly higher than R^2 estimates associated with either physical q or total q. For example, PI q explains 21% of the variation in physical investment, 36% of the variation in R&D investment, and 42% of the variation in total investment. These R^2 estimates are between 21% and 64% (i.e., four and 14 percentage points) higher than R^2 estimates associated with other proxies for q. Furthermore, differences in R^2 estimates are statistically

[7] Erickson and Whited (2012) state that using different divisors for investment and q implies the identification assumption that the regression coefficient does not equal zero (i.e., $\beta \neq 0$) is close to being violated, and no estimator provides reliable estimates when it is nearly unidentified. For the analysis of a large cross-section, they advise using the same divisor for all regression variables.

significant; all ΔR^2 estimates are between 14 and 24 times larger than their associated standard errors.[8]

Since PI q's explanatory power is due in part to the inclusion of the replacement cost of patent capital, PI q's outperformance should be stronger when focusing on firms with patent capital. To investigate this hypothesis, Panel B of Table 1.2 presents results for firms with patent capital at any point during the sample period. All R^2 estimates associated with PI q in Panel B are between 4% and 30% larger than corresponding R^2 estimates in Panel A. Furthermore, Panel B shows that R^2 estimates associated with PI q are between 34% and 65% (i.e., seven and 15 percentage points) higher than R^2 estimates associated with other proxies for q. ΔR^2 estimates show that these differences are again highly significant. The results in Panel B are consistent with the hypothesis that PI q's explanatory power should be relatively stronger when focusing on firms with patent capital.

Overall, Table 1.2 shows that PI q explains significantly more variation in all investment types than either physical q or total q. PI q's outperformance is stronger when focusing on firms with patent capital and is strongest when focusing on R&D investment. The latter result is likely driven by the fact that R&D investment is the investment type most closely associated with the development of patent capital. Firms that engage in R&D investment are more likely to have patent capital than firms that do not engage in R&D investment. By including patent capital in these firms' estimates of q, I am alleviating a potentially substantial source of measurement error in q for these firms, which leads to a larger improvement when predicting R&D investment.[9]

[8]Within R^2 estimates are materially lower than in Peters and Taylor (2017) due to differences in how within R^2 estimates are calculated. In Peters and Taylor (2017), within R^2 estimates are estimated within firms but not within years. I estimate within R^2 estimates within firms and years. I thank Ryan Peters for helping me resolve this inconsistency.

[9]In addition to physical investment and R&D investment, Peters and Taylor (2017) also analyze intangible investment, which they define as R&D expenses (set to zero if missing) plus 30% of SG&A expenses, and physical plus intangible (total investment (PT)). In Table A.1, I show that PI q explains significantly more variation in intangible investment and total investment (PT) than either physical q or total q. Consistent with the results in Table 1.2, this outperformance is stronger when focusing on firms with patent capital.

1.4.2 Bias-corrected results

As discussed above, coefficient estimates on q are biased when using OLS (Erickson and Whited, 2000). This bias stems from two sources of measurement error. First, Tobin's q is not perfectly observable to the econometrician. Second, any estimate of Tobin's q measures average q, not marginal q, which should be the true determinant of new investment in q theory. To account for this bias, Erickson and Whited (2000) use a two-step generalized method of moments (GMM) estimator to obtain bias-corrected coefficient estimates on q (Erickson and Whited, 2002). While the resulting coefficients are unbiased, Erickson et al. (2014) build upon the GMM framework and develop a high-order cumulant estimator. Cumulant estimators have closed-form solutions, so the researcher does not have to choose starting values in the data. This is important because GMM results can be highly sensitive to starting value choices (Erickson and Whited, 2012). Cumulant estimators provide unbiased estimates of β in the following errors-in-variables model:

$$y_{it} = q_{it}\beta + u_{it} \tag{1.12}$$

$$x_{it} = q_{it} + e_{it}, \tag{1.13}$$

in which y_{it} is investment, and x_{it} is an observable proxy for the true, unobservable q_{it}. The error terms, u_{it} and e_{it}, are independent of each other and of q_{it}.

One might wonder why a new proxy for q is necessary if the above procedure accounts for measurement error. Since investment and q share a denominator, both variables have measurement error. The two measurement errors are correlated with each other, which violates the assumption that u_{it} and e_{it} are independent of each other.[10] To that end, an improved proxy for q can still improve the observed relation between investment and q in a bias-corrected setting.

[10]For a detailed discussion, please see footnote 10 in Peters and Taylor (2017).

Table 1.3 presents bias-corrected results from cumulant estimator regressions of investment on lagged q, firm fixed effects, and year fixed effects. Panel A presents results for all firms, and Panel B presents results for firms with patent capital.[11,12] Obtaining bias-corrected coefficients on q is important because when regressing investment on q, the coefficient on q can be interpreted as a determinant of the elasticity of investment with respect to q (Whited, 1994; Erickson and Whited, 2000). Previous work has found coefficients on q, and thus elasticities of investment with respect to q, to be much lower than expected (Philippon, 2009). However, a comparison of q-slopes within each investment type shows that with only one exception in each panel, elasticities are higher when using PI q than when using other proxies for q. Furthermore, differences in coefficient estimates within investment types are generally larger when concentrating on firms with patent capital. Although all coefficient estimates on q are smaller than the theorized coefficient of one (Hayashi and Inoue, 1991), coefficients on PI q are indeed closer to one than coefficients on other proxies for q.

Importantly, the relatively higher investment-PI q sensitivity does not come at the expense of explanatory power. The cumulant estimator provides two useful statistics for understanding how well a mismeasured proxy performs. The first is ρ^2, which is the within R^2 estimate from the hypothetical regression of investment on marginal q, i.e., the within R^2 estimate from equation (1.12). The second is τ^2, which is the within R^2 estimate from the hypothetical regression of estimated q on marginal q, i.e., the within R^2 estimate from equation (1.13). If hypothetical marginal q perfectly explains investment, ρ^2 equals 100%. Likewise, if any proxy is a perfect one for marginal q, τ^2 equals 100%.

Panel A of Table 1.3 shows that within each investment type, ρ^2 and τ^2 estimates associated with PI q are always larger than those associated with other proxies for q. When using PI q, marginal q explains 39%, 59%, and 61% of the variation in physical investment, R&D

[11] All regression variables have been demeaned to account for firm fixed effects and year fixed effects.

[12] Unless otherwise specified, I use a third-order cumulant estimator, which results in an exactly identified system. Erickson et al. (2017) suggest that the order cumulant a researcher uses is an empirical choice. All Sargan-Hansen J statistics (unreported) associated with higher-order cumulants reject the null hypothesis that the overidentifying restrictions are valid. Robustness tests (Table 1.7) show that PI q comfortably outperforms alternative proxies for q in specifications that exploit higher-order cumulants.

investment, and total investment. These ρ^2 estimates are between 12% and 36% (i.e., four and 16 percentage points) higher than those associated with other proxies for q. In addition, when using PI q to predict physical investment, R&D investment, and total investment, τ^2 estimates are 53%, 62%, and 69%. These percentages are between 9% and 26% (i.e., four and 11 percentage points) higher than those associated with other proxies for q.

Panel B shows that when focusing on firms with patent capital, PI q's relative outperformance is again stronger than when focusing on all firms. All ρ^2 and τ^2 estimates associated with PI q in Panel B are larger than corresponding estimates in Panel A. Furthermore, Panel B shows that when comparing ρ^2 and τ^2 estimates associated with PI q to those associated with other proxies for q, differences are generally larger than in Panel A.

The results in Table 1.3 show that bias-corrected coefficients are almost always higher when using PI q. These results also show that for all investment types, PI q is a better proxy for marginal q than either physical q or total q. PI q's outperformance is again stronger when focusing on firms with patent capital and is strongest when focusing on R&D investment. Overall, Table 1.3 shows that even when using this bias-correcting methodology, results associated with PI q are more consistent with q theory than results associated with other proxies for q.[13]

1.4.3 Subsample analysis

Figure 1.3 shows that average firm-level patent intensity varies significantly across industries and has generally been increasing over time. Consistent with observation totals and percentages in Figure 1.2, firms in healthcare and high-tech have the highest average levels of patent intensity. Since PI q's outperformance in the full sample is driven in part by the inclusion of the replacement cost of patent capital, the investment-PI q relation should be

[13]Table A.2 shows that when examining intangible investment and total investment (PT), bias-corrected coefficients, ρ^2 estimates, and τ^2 estimates associated with PI q are always higher than those associated with other proxies for q. Consistent with the results in Table 1.3, results associated with PI q are relatively stronger when focusing on firms with patent capital.

relatively stronger in industries and time periods with more patent capital. To test this hypothesis, in this subsection, I investigate the investment-q relation within industries and over time.[14]

1.4.3.1. Industry-level analysis

Figures 1.4, 1.5, and 1.6 present estimates from regressions of investment on lagged q, firm fixed effects, and year fixed effects after sorting firms by industry. Industries within each panel are sorted from lowest (top) to highest (bottom) with respect to their average firm-level patent intensity.

Figure 1.4 presents results from regressions of physical investment on different proxies for q. Panels A and B show that differences in R^2 and ρ^2 estimates are negligible in the three industries with the lowest levels of patent intensity (i.e., other, consumer, and manufacturing), but in the two industries with the highest levels of patent intensity (i.e., high-tech and healthcare), R^2 and ρ^2 estimates associated with PI q are up to 11 percentage points higher than those associated with other proxies. Panel C shows that PI q is a better proxy for marginal q than other proxies in all five industries, and differences in τ^2 estimates generally increase in patent intensity. Panel D shows that β estimates, or bias-corrected coefficient estimates on q, are highest when using total q and lowest when using physical q. The results in Panel D are consistent with those in the full sample.

The results associated with PI q in Figure 1.5, which focuses on R&D investment, are relatively stronger than those in Figure 1.4. Panels A and B once again show that R^2 and ρ^2 estimates associated with PI q are highest in the majority of industries, and differences in R^2 and ρ^2 estimates are larger in industries with more patent capital. For example, in high-tech and healthcare, R^2 estimates associated with PI q are 13 and 21 percentage points higher than R^2 estimates associated with total q. Panel C shows that differences in τ^2 estimates are negligible in the three industries with the lowest levels of patent capital.

[14] All regression variables are winsorized either within industries or time periods. Winsorization over the full sample could still produce extreme outliers when regressions are estimated within industries or time periods.

However, τ^2 estimates associated with PI q are at least 10 percentage points higher than τ^2 estimates associated with both physical q and total q in high-tech and are over 20 percentage points higher than τ^2 estimates associated with total q in healthcare. Panel D shows that β estimates associated with PI q are highest in all five industries, and differences in β estimates generally increase in patent intensity.

Lastly, Figure 1.6 presents results from regressions of total investment on different proxies for q. Panel A shows that differences in R^2 estimates are over 10 percentage points in high-tech and reach nearly 20 percentage points in healthcare. Panels B and C show that ρ^2 and τ^2 estimates associated with PI q are mostly similar to those associated with physical q but are always much higher than those associated with total q. Panel D shows that once again, in all five industries, β estimates associated with PI q are higher than β estimates associated with other proxies. Furthermore, differences in β estimates are generally larger in industries with more patent capital.

The results in Figures 1.4, 1.5, and 1.6 show that R^2, ρ^2, τ^2, and β estimates associated with PI q are almost always higher than those associated with other proxies for q. Importantly, differences in these estimates are larger in industries with higher levels of patent capital.

1.4.3.2. Time period analysis

As discussed above, intangible capital has become a larger component of total capital over time. Andrei et al. (2019) show that the explanatory power of both physical q and total q also increase over time. Given the increase in capital intangibility in recent decades, I expect the explanatory power of PI q to increase even faster than that of other proxies for q. I test this expectation by regressing investment on lagged q, firm fixed effects, and year fixed effects over rolling windows. In an effort to balance a reduction in noise and plot a sufficient number of estimates, I present results using 20-year rolling windows.[15]

[15]In unreported tests, I find that my results are similar when using 15-year or 25-year rolling windows.

Figure 1.7 plots estimates from regressions of physical investment on different proxies for q. Each year in the plot represents the last fiscal year in the rolling window. Panels A, B, and C show that R^2, ρ^2, and τ^2 estimates associated with PI q were similar to those associated with other proxies in the first half of the sample. Over time though, R^2, ρ^2, and τ^2 estimates associated with PI q generally increase at a faster rate than those associated with either physical q or total q. Panel D shows that consistent with the main results, bias-corrected coefficient estimates on PI q are always higher than those on physical q and always lower than those on total q. Although all β estimates decline over time, β estimates on PI q improve relative to those on both physical q and total q. Declining coefficients on q over time are well-documented and may be the result of changes in market competition and corporate governance (Gutiérrez and Philippon, 2016, 2017).[16]

The results in Figure 1.8 show that the growing outperformance of PI q is larger when analyzing R&D investment. Panels A and C show that differences in R^2 and τ^2 estimates were small in the mid-1990s, but recent R^2 and τ^2 estimates associated with PI q are about 10 percentage points higher than those associated with other proxies for q. Panel B shows that ρ^2 estimates associated with PI q are more recently around six and 15 percentage points higher than those associated with physical q and total q. Panel D shows that differences in β estimates have also grown over time.

The growing outperformance of PI q over time is also salient in Figure 1.9, which focuses on total investment. Panel A shows that by the end of the sample, R^2 estimates associated with PI q are 10 and 16 percentage points higher than those associated with physical q and total q. Panels B and C show that ρ^2 and τ^2 estimates associated with PI q also grow at a faster rate than those associated with other proxies for q. Panel D shows that β estimates associated with PI q decline over time at a slower rate than β estimates associated with either physical q or total q.

[16] See Chen and Chen (2012), Peters and Taylor (2017), and Andrei et al. (2019) for examples of the declining coefficient estimate on q.

Figures 1.7, 1.8, and 1.9 show that over 20-year rolling windows and across investment types, the outperformance of PI q has grown over time along with the importance of patent capital. This finding is consistent with the implication in Andrei et al. (2019) that as intangible capital has become more important over time, the explanatory power of different proxies for q has been determined by their ability to accurately estimate firm-level intangible capital.

1.5 Investment, q, and cash flow

The q theory of investment states that q should be the sole determinant of new investment. However, many empirical tests show that when regressing investment on q and cash flow, there is a positive coefficient on cash flow (Hassett and Hubbard, 1997; Caballero, 1999).

There are three main explanations for this positive cash flow coefficient. The first explanation is that a positive cash flow coefficient reflects the existence of financing constraints (Fazzari et al., 1988; Brown et al., 2009). If q is a sufficient proxy for investment opportunities, but firms cannot obtain external financing, investment will depend on internal cash flow. The second explanation is that measurement error in q results in a positive cash flow coefficient (Erickson and Whited, 2000; Gomes, 2001). If q is not a sufficient proxy for investment opportunities, we might erroneously obtain a positive cash flow coefficient. The third explanation is that cash flow provides additional information about future investment opportunities (Gilchrist and Himmelberg, 1995; Alti, 2003). In all specifications, q is lagged one period from investment, but since cash flow is concurrent with investment, cash flow might include information about future investment opportunities not contained in q.

Given the importance of the extensive investment-cash flow literature, in this section, I investigate how PI q affects the investment-cash flow relation.

1.5.1 Full sample

Since R&D is expensed before taxes, I adjust cash flow to reflect funds available before any investment is made:

$$Cash\ flow_{it} = \frac{IB_{it} + DP_{it} + R\&D_{it}(1-\kappa)}{K^{phy}_{i,t-1} + K^{int^{PI}}_{i,t-1}}, \tag{1.14}$$

in which IB is income before extraordinary items, DP is depreciation and amortization, $R\&D$ is research and development, and $(1-\kappa)$ is one minus the marginal tax rate. Following Peters and Taylor (2017), I estimate κ using simulated marginal tax rates from Graham (1996a,b), and if not available, I use 30%. When regressing investment on other proxies for q, the denominator of cash flow matches the denominator of those other proxies.

Table 1.4 presents results from regressions of investment on q, cash flow, firm fixed effects, and year fixed effects. Panel A presents results for all firms. The first three columns show that although each proxy for q is able to break the physical investment-cash flow relation, the cash flow coefficient is highest when controlling for PI q. The middle three columns show that when controlling for any proxy for q, R&D investment is negatively associated with cash flow, but again, the cash flow coefficient is highest when controlling for PI q. The last three columns show that when predicting total investment, the cash flow coefficient is highest, and highly significant, when controlling for PI q. Interestingly, although PI q is a better proxy for all investment types, cash flow coefficients are always higher, albeit insignificantly, when controlling for PI q than when controlling for physical q or total q.

Panel B of Table 1.4 shows that when focusing on firms with patent capital, differences in cash flow coefficients are larger. When predicting physical investment, controlling for PI q leads to a cash flow coefficient that is nearly twice as high than when controlling for physical q or total q. The middle three columns show that when regressing R&D investment on q

and cash flow, the cash flow coefficient is again highest when controlling for PI q. In the last three columns, total investment is most sensitive to cash flow when controlling for PI q.

Table 1.4 shows that when regressing investment on q and cash flow, controlling for PI q leads to higher cash flow coefficients than when controlling for other proxies for q. Table 1.4 also shows that differences in cash flow coefficients are larger when focusing on firms with patent capital. In other words, the results in Table 1.4 show that controlling for a better proxy for q, which is PI q in this case, does not necessarily lead to smaller cash flow coefficients, as previously conjectured (e.g., Kaplan and Zingales, 1997).

1.5.2 Why does controlling for PI q increase cash flow coefficients?

If PI q is a better proxy for Tobin's q, why are cash flow coefficients relatively higher when controlling for PI q? Recall that when regressing investment on q and cash flow, the denominators of all regression variables are the same. In other words, not only do investment-q correlations change when controlling for different proxies for q, but investment-cash flow correlations also change when controlling for different proxies for q. To understand how investment-cash flow correlations change when controlling for different proxies for q, Table 1.5 presents correlations between demeaned investment, lagged q, and cash flow variables.

Panel A presents correlations for regression variables associated with physical investment. The correlation between physical investment and PI q is 0.45, which is between 10% and 19% higher than correlations between physical investment and other proxies for q (i.e., 0.41 and 0.38). However, correlations between physical investment and cash flow vary much more. When scaled by the denominator of PI q, the correlation between physical investment and cash flow is 0.30, which is between 18% and 30% higher than correlations between physical investment and other cash flow variables (i.e., 0.23 and 0.25). Thus, when scaled by the denominator of PI q, the physical investment-cash flow correlation increases much more than the physical investment-q correlation.

Panels B and C of Table 1.5 show that differences in investment-cash flow correlations are even larger when focusing on R&D investment and total investment. Correlations between PI q and both R&D investment and total investment are 0.60 and 0.64, which are between 13% and 28% higher than those when using physical q and total q. However, when scaled by the denominator of PI q, correlations between cash flow and both R&D investment and total investment are 0.31 and 0.36, which are between 14% and 56% higher than those when scaled by the denominator of either physical q or total q.

Panels A through C of Table 1.5 show that by scaling regression variables by the denominator of PI q, investment-cash flow correlations increase relatively more than investment-q correlations. These increased correlations may be why bias-corrected cash flow coefficients, which are reproduced in Panel D of Table 1.5, are higher when controlling for PI q than when controlling for other proxies for q. Developing a deeper understanding for how investment, q, and cash flow relations change as the denominators of these variables change is an interesting question for future research.

1.6 Robustness

In this section, I show that my results are robust when using alternative patent depreciation rates, alternative estimates for the marginal q of new patents, or higher-order cumulants. I also show that PI q's performance is driven by both the replacement cost of patent capital and on-balance sheet intangible capital. Lastly, I find that PI q performs best when the replacement cost of intangible capital is estimated using just the replacement cost of patent capital and on-balance sheet intangible capital.

1.6.1 Changes to patent capital

When constructing PI q, I make assumptions regarding patent capital depreciation rates and marginal q estimates of new patents. In this subsection, I modify these assumptions and show that my results are largely unchanged.

In my main results, I depreciate the replacement cost of patent capital using industry-specific R&D depreciation rates (Li, 2012). Although R&D investment is closely related to subsequently-issued patents, the depreciation rates of the two may not be identical. Panel A of Table 1.6 presents results when using alternative patent capital depreciation rates. The first row presents the main results. Rows two through five present results when using depreciation rates between 15% and 30%. The sixth row doubles all industry-specific depreciation rates. The results remain qualitatively unchanged in all rows.

One of the strongest assumptions I make when estimating the replacement cost of patent capital is a presumed marginal q of new patents of 1.5 across firms and time. Depending on the efficiency of the firm or the competitiveness of the industry or time period, marginal q may be either lower or higher than 1.5. Panel B presents results when using alternative estimates for the marginal q of new patents. The first row presents the main results. In rows two through five, I change the marginal q of new patents to 1.0, 1.25, 1.75, or 2.0. The results in the latter four rows are largely unchanged from the main results. Importantly, these results highlight how different estimates for the marginal q of new patents do not materially affect the main results.

Overall, Table 1.6 shows that PI q's performance is robust to changes in the assumptions used to estimate the replacement cost of patent capital. Specifically, PI q's performance is essentially unaffected by changes in the depreciation rates of patent capital or changes in the marginal q of new patents. These results show that the inclusion of the replacement cost of patent capital is much more important to the performance of PI q than a particular patent capital depreciation rate or marginal q of new patents.

1.6.2 Higher-order cumulants

For all prior cumulant estimator results, I use a third-order cumulant, which results in an exactly identified system of equations. In Table 1.7, I present results from the main investment specification using higher-order cumulants.

The first row in each panel presents the main results. Panel A presents results associated with PI q, Panel B presents results associated with physical q, and Panel C presents results associated with total q. Across panels and within investment types, a comparison of coefficient estimates, ρ^2 estimates, and τ^2 estimates reveal that those associated with PI q are almost always higher than those associated with either physical q or total q.

In summary, Table 1.7 shows that regardless of the order cumulant used, results associated with PI q are more consistent with q theory than those associated with other proxies.

1.6.3 Changes to intangible capital

My estimate of intangible capital includes both patent capital and on-balance sheet intangible capital, but since on-balance sheet intangible capital is also included in total q, the novelty of PI q comes from the inclusion of patent capital. To isolate the effect of each component of intangible capital on PI q's performance, I regress investment on PI q after excluding either patent capital or on-balance sheet intangible capital.

Panel A of Table 1.8 presents the results. The main results are in the first row. The results in the second and third rows of Panel A reflect the exclusion of patent capital or on-balance sheet intangible capital. In both rows, all estimates decline to similar levels. In other words, patent capital and on-balance sheet intangible capital are about equally important to PI q's performance.

Since the sum of patent capital and on-balance sheet intangible capital is unlikely to perfectly measure intangible capital, it is possible that the inclusion of alternative components of intangible capital improves PI q's performance. In Panel B of Table 1.8, I present results from regressions of investment on PI q after adding estimates of knowledge capital, organization capital, or both from Peters and Taylor (2017) or Ewens et al. (2020) to PI q. The first row presents the original results from regressions of investment on PI q. The second through seventh rows present results using alternative estimates of PI q. The inclusion of knowledge capital worsens the performance of PI q more than the inclusion of organization capital. When both knowledge capital and organization capital are included, the performance of PI q declines even further.

Overall, Table 1.8 shows that PI q's performance is dependent on both patent capital and on-balance sheet intangible capital. Importantly, this table shows that PI q performs best when the replacement cost of intangible capital is estimated using just patent capital and on-balance sheet intangible capital, both of which do not require assumptions about how much intangible capital is created through associated expenses.

1.7 Conclusion

In this paper, I construct a new proxy for Tobin's q, which I call PI q, that includes the replacement cost of patent capital. The main result is that PI q is a better proxy for q than two commonly-used proxies for q. Specifically, I show that PI q explains significantly more variation in firm-level investment and is more closely related to hypothetical marginal q than other proxies for q. I also show that bias-corrected coefficient estimates on q are almost always higher when using PI q. These results are stronger when focusing on industries and time periods with more patent capital.

Although PI q is a better proxy for q than other proxies for q, I show that controlling for PI q leads to relatively higher, not lower, cash flow coefficients. Not only does this result show that controlling for a better proxy for q can lead to higher cash flow coefficients, but this result also shows that when scaled differently, cash flow may be more important for predicting investment than previously thought.

In summary, these results imply that including market-based estimates of the replacement cost of intangible capital is important for constructing a better proxy for Tobin's q.

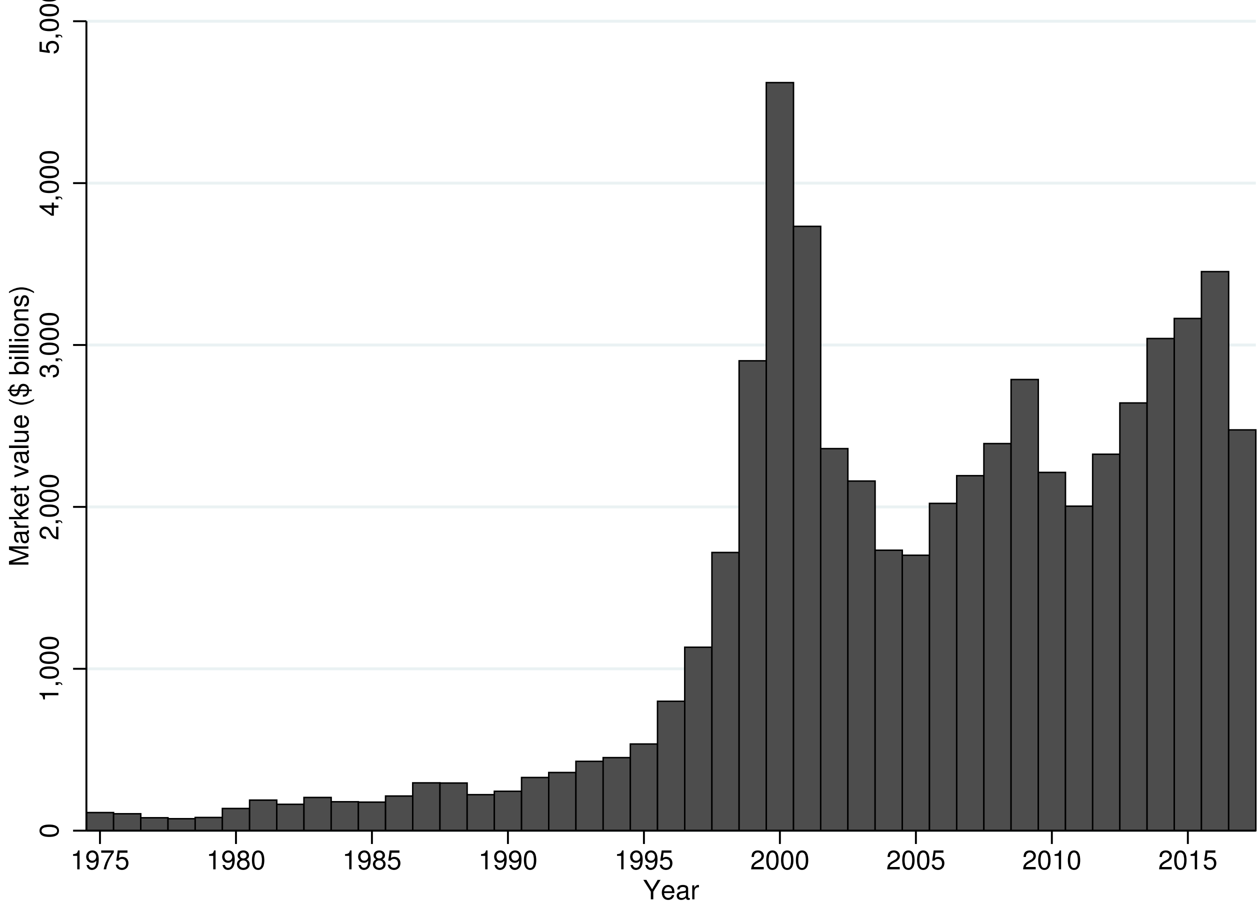

Figure 1.1. Market value of patents issued to publicly-traded firms

This figure presents the estimated annual market value of patents issued to publicly-traded firms between 1975 and 2017 (Kogan et al., 2017; Stoffman et al., 2020). Since patent data end on September 12, 2017, the 2017 market value total reflects that truncation.

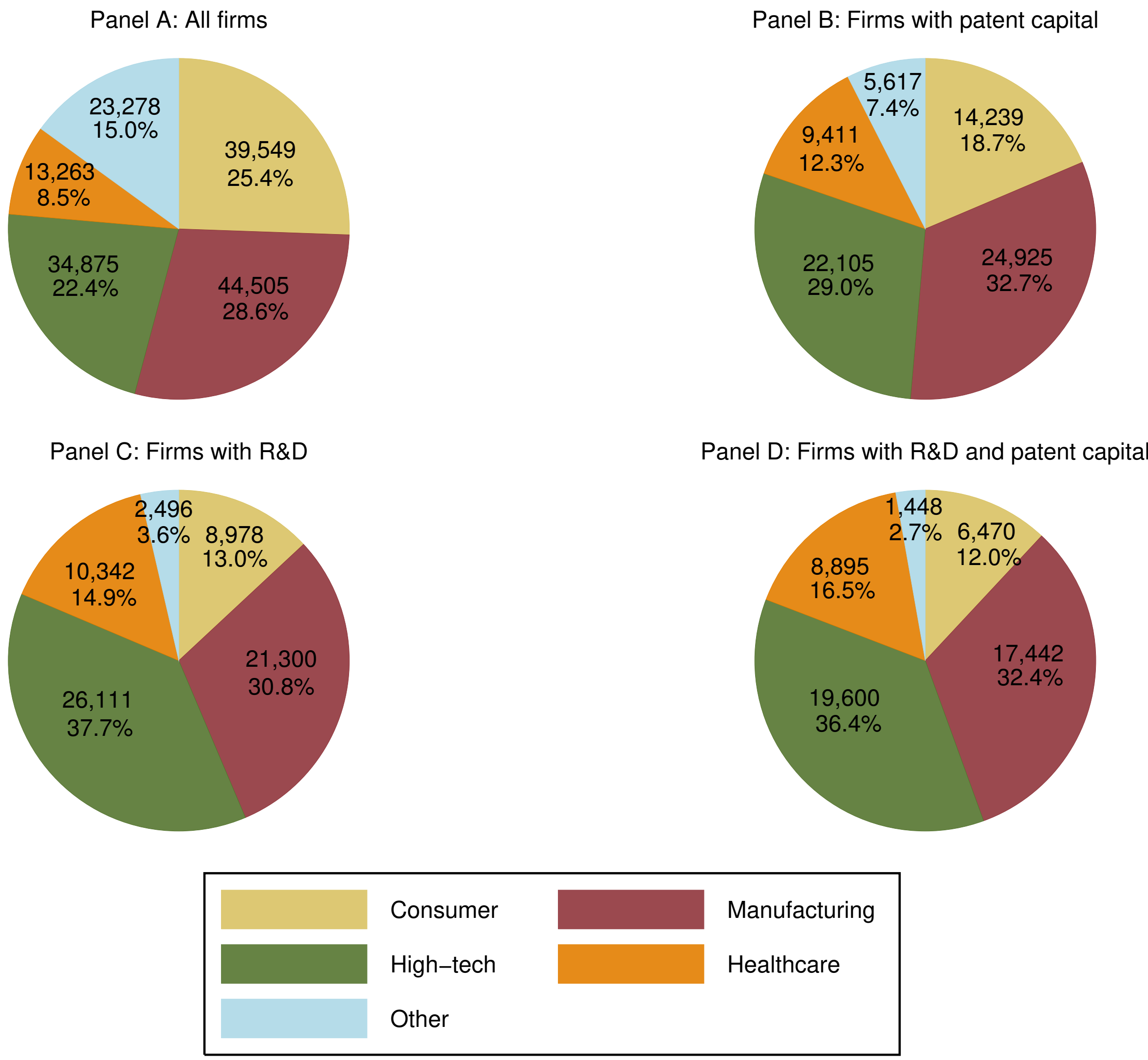

Figure 1.2. Observations by industry

This figure presents firm-year observation totals and percentages in five Fama-French industries. Panel A presents totals and percentages for all firms. Panel B presents totals and percentages for firms with patent capital at any point during the sample. Panel C presents totals and percentages for observations with R&D investment. Panel D presents totals and percentages for observations with R&D investment and patent capital at any point during the sample.

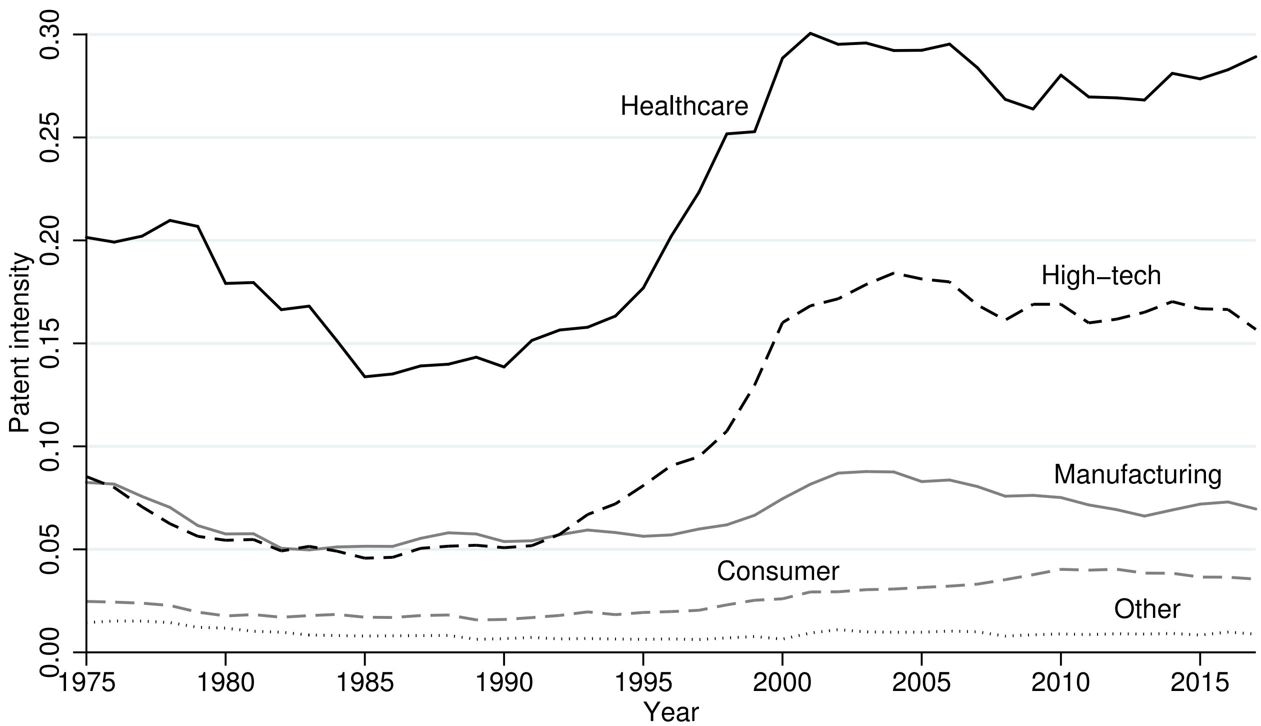

Figure 1.3. Patent intensity across industries

This figure presents average firm-level patent intensity across five Fama-French industries over time. Patent intensity, which is calculated and plotted each fiscal year, is patent capital divided by total capital. Total capital is the book value of gross property, plant, and equipment plus patent capital and on-balance sheet intangible capital.

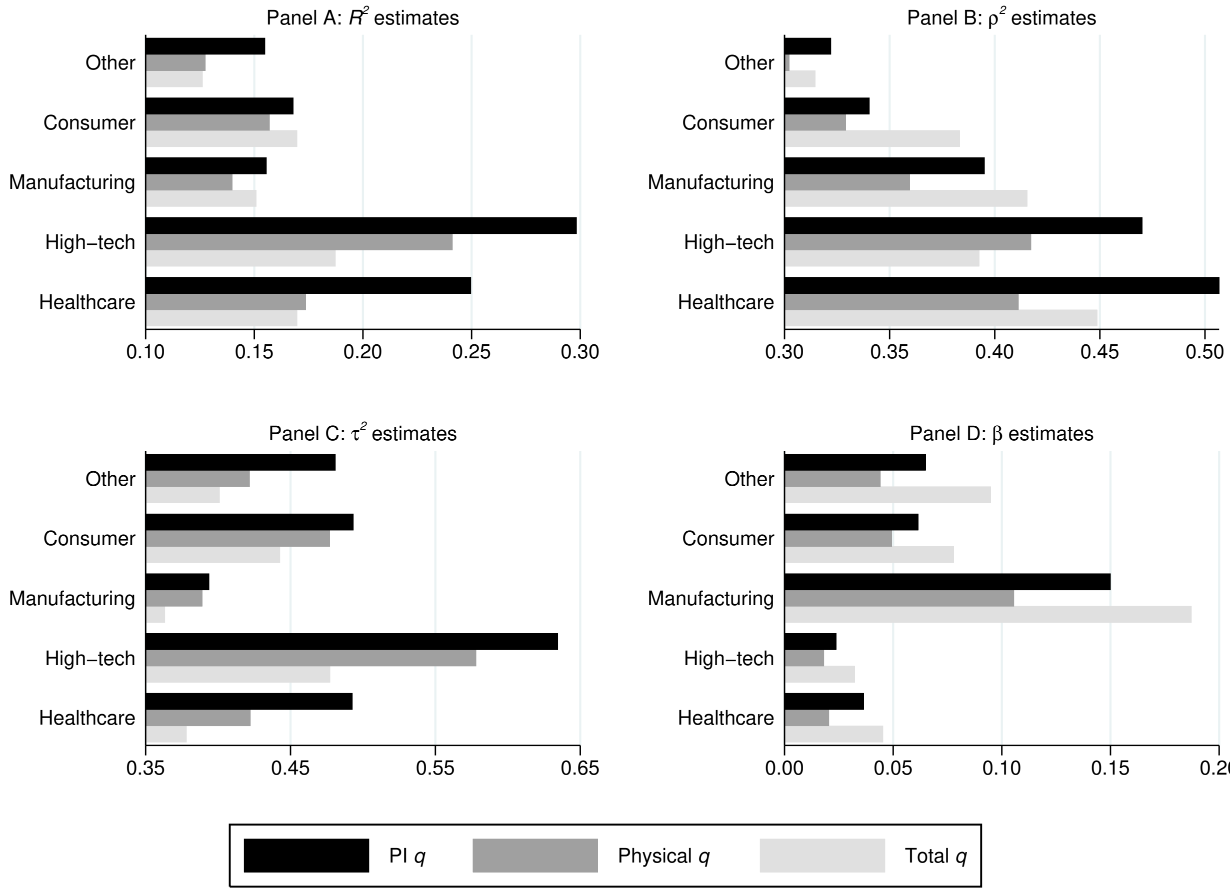

Figure 1.4. Physical investment-q relation across industries

This figure presents results from regressions of physical investment on lagged q, firm fixed effects, and year fixed effects after sorting firms into five Fama-French industries. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). Physical investment is capital expenditures scaled by the denominator of lagged q being regressed on by investment. Panel A presents within R^2 estimates from OLS regressions, which are ordinary R^2 estimates from estimating OLS on the transformed data. Panel B presents ρ^2 estimates, which are within R^2 estimates from hypothetical regressions of physical investment on marginal q. Panel C presents τ^2 estimates, which are within R^2 estimates from hypothetical regressions of q on marginal q. Panel D presents β estimates, which are bias-corrected coefficient estimates on q from cumulant estimator regressions of physical investment on q. Industries are ranked from lowest (top) to highest (bottom) with respect to their average firm-level patent intensity.

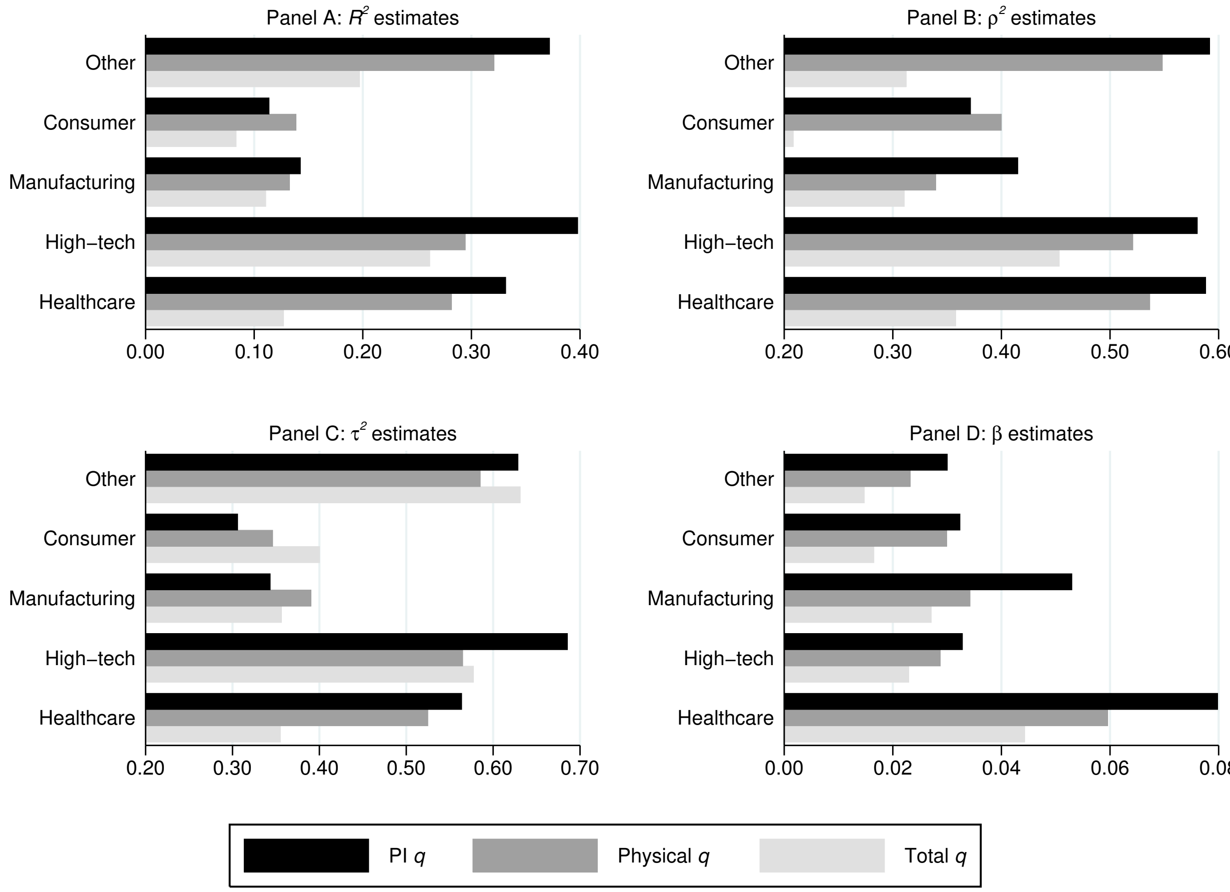

Figure 1.5. R&D investment-q relation across industries

This figure presents results from regressions of R&D investment on lagged q, firm fixed effects, and year fixed effects after sorting firms into five Fama-French industries. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). R&D investment is research and development expenses scaled by the denominator of lagged q being regressed on by investment. Panel A presents within R^2 estimates from OLS regressions, which are ordinary R^2 estimates from estimating OLS on the transformed data. Panel B presents ρ^2 estimates, which are within R^2 estimates from hypothetical regressions of R&D investment on marginal q. Panel C presents τ^2 estimates, which are within R^2 estimates from hypothetical regressions of q on marginal q. Panel D presents β estimates, which are bias-corrected coefficient estimates on q from cumulant estimator regressions of R&D investment on q. Industries are ranked from lowest (top) to highest (bottom) with respect to their average firm-level patent intensity.

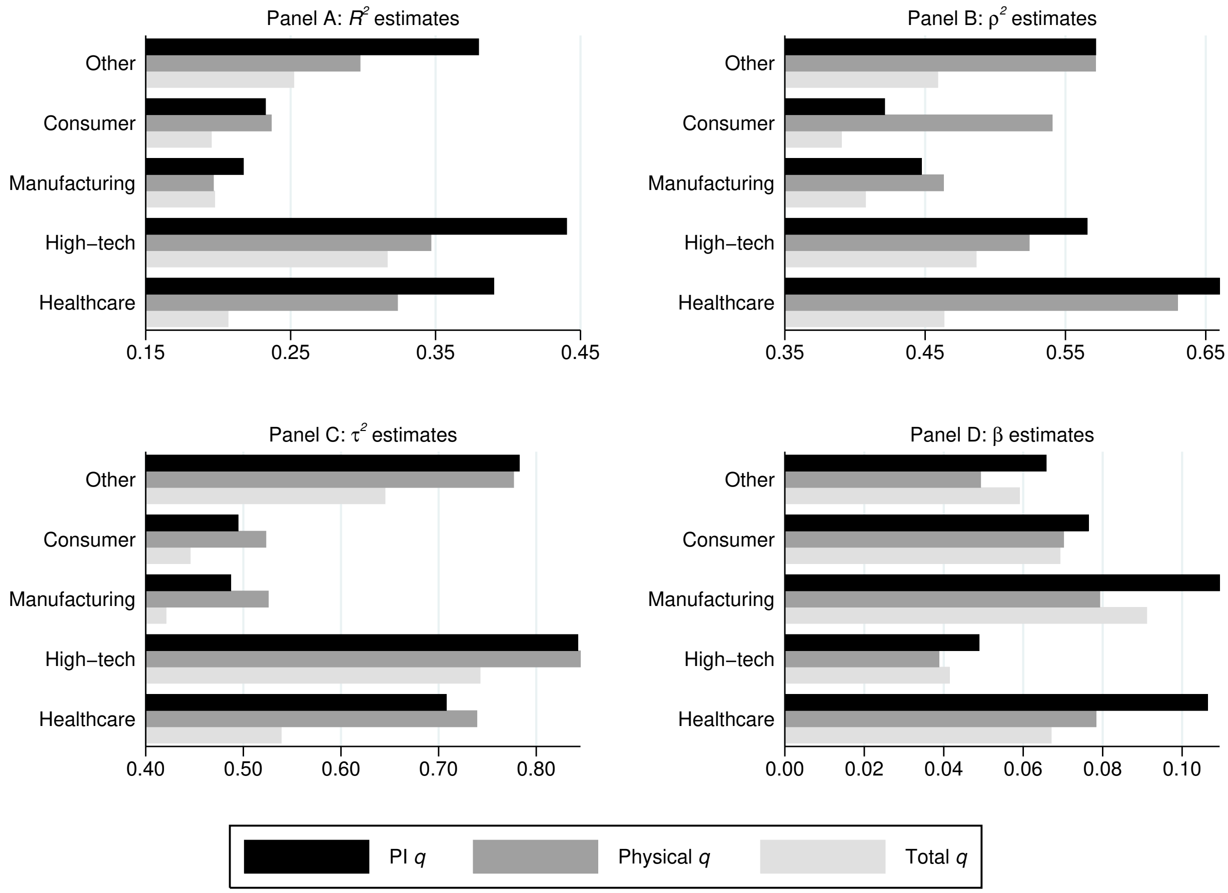

Figure 1.6. Total investment-q relation across industries

This figure presents results from regressions of total investment on lagged q, firm fixed effects, and year fixed effects after sorting firms into five Fama-French industries. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). Total investment is capital expenditures plus research and development expenses scaled by the denominator of lagged q being regressed on by investment. Panel A presents within R^2 estimates from OLS regressions, which are ordinary R^2 estimates from estimating OLS on the transformed data. Panel B presents ρ^2 estimates, which are within R^2 estimates from hypothetical regressions of total investment on marginal q. Panel C presents τ^2 estimates, which are within R^2 estimates from hypothetical regressions of q on marginal q. Panel D presents β estimates, which are bias-corrected coefficient estimates on q from cumulant estimator regressions of total investment on q. Industries are ranked from lowest (top) to highest (bottom) with respect to their average firm-level patent intensity.

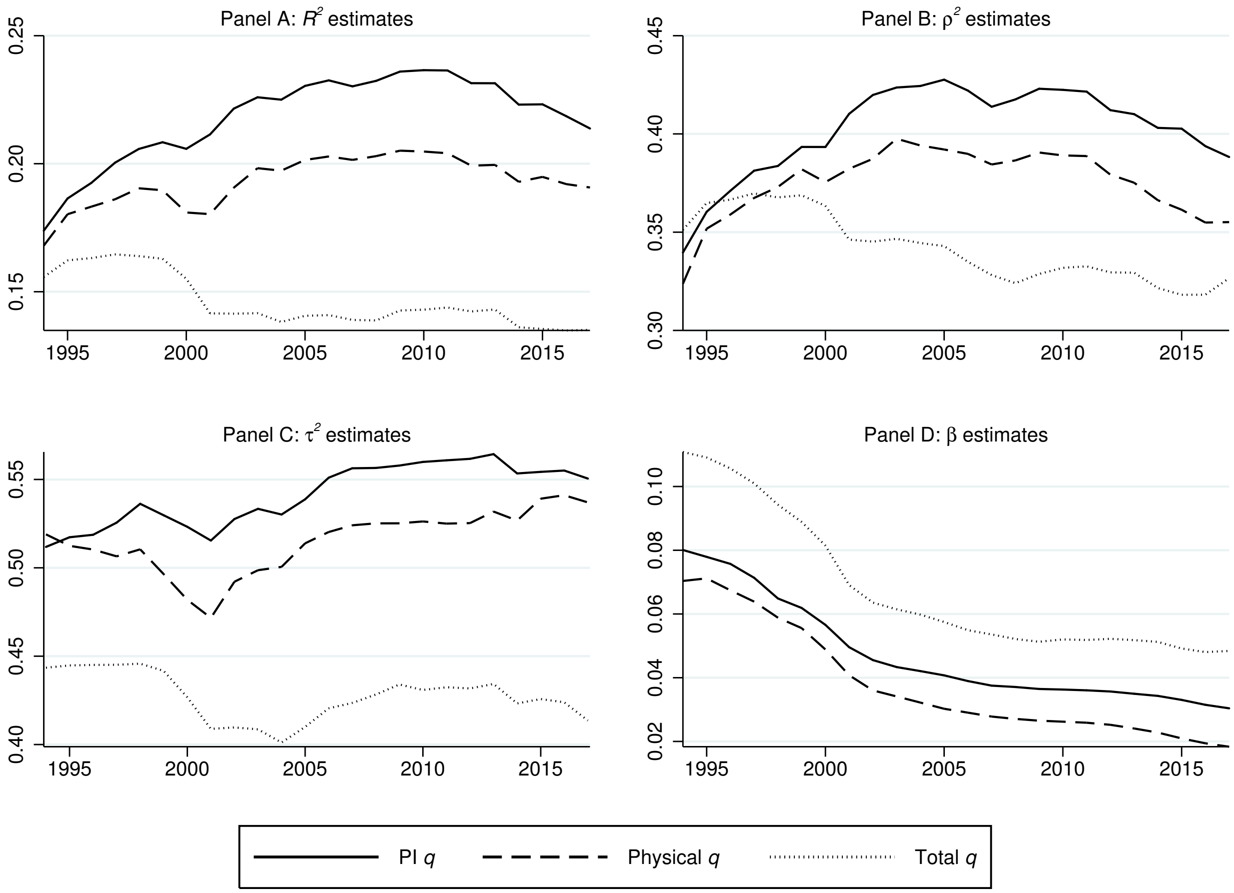

Figure 1.7. Physical investment-q relation over time

This figure presents results from regressions of physical investment on lagged q, firm fixed effects, and year fixed effects over 20-year rolling windows. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). Physical investment is capital expenditures scaled by the denominator of lagged q being regressed on by investment. Panel A presents within R^2 estimates from OLS regressions, which are ordinary R^2 estimates from estimating OLS on the transformed data. Panel B presents ρ^2 estimates, which are within R^2 estimates from hypothetical regressions of physical investment on marginal q. Panel C presents τ^2 estimates, which are within R^2 estimates from hypothetical regressions of q on marginal q. Panel D presents β estimates, which are bias-corrected coefficient estimates on q from cumulant estimator regressions of physical investment on q. Each year represents the last year in the 20-year window.

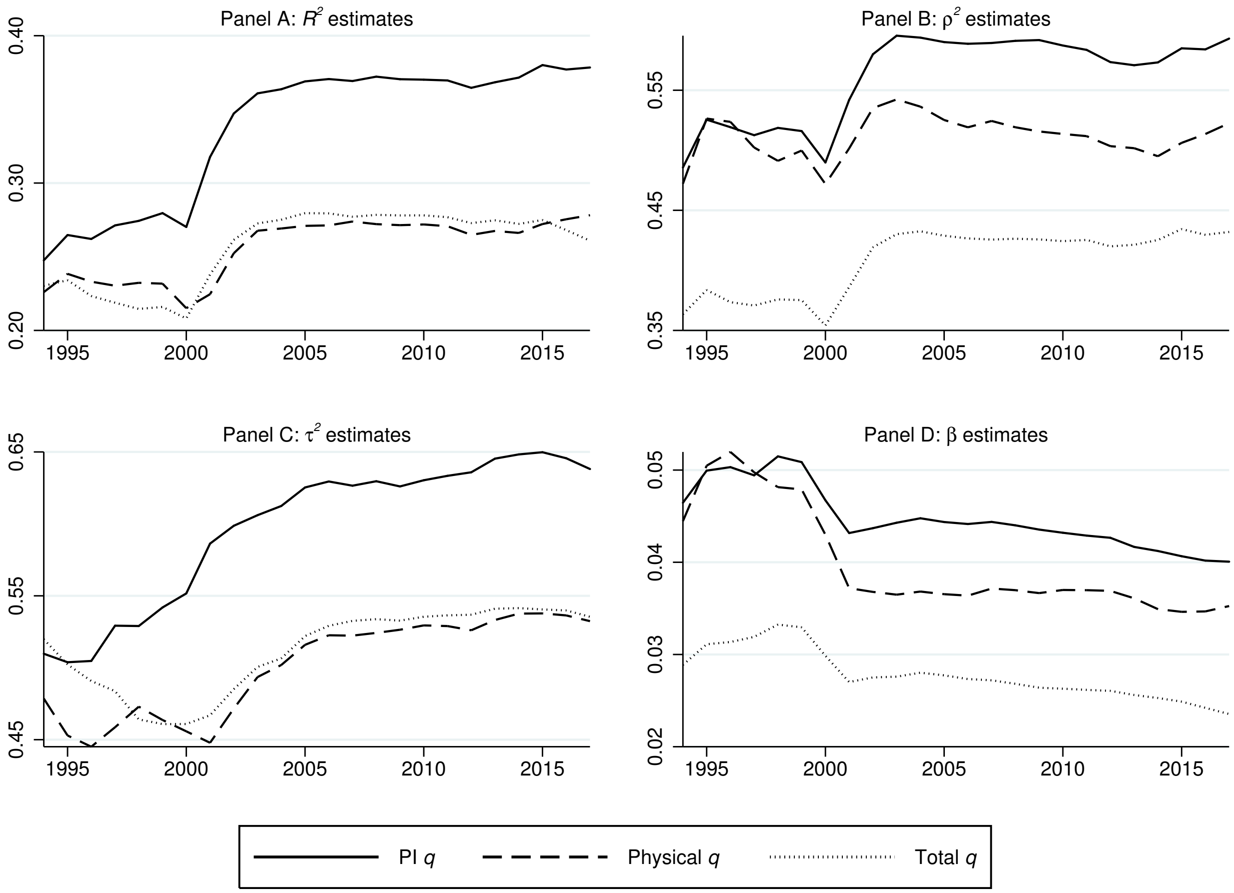

Figure 1.8. R&D investment-q relation over time

This figure presents results from regressions of R&D investment on lagged q, firm fixed effects, and year fixed effects over 20-year rolling windows. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). R&D investment is capital expenditures scaled by the denominator of lagged q being regressed on by investment. Panel A presents within R^2 estimates from OLS regressions, which are ordinary R^2 estimates from estimating OLS on the transformed data. Panel B presents ρ^2 estimates, which are within R^2 estimates from hypothetical regressions of R&D investment on marginal q. Panel C presents τ^2 estimates, which are within R^2 estimates from hypothetical regressions of q on marginal q. Panel D presents β estimates, which are bias-corrected coefficient estimates on q from cumulant estimator regressions of R&D investment on q. Each year represents the last year in the 20-year window.

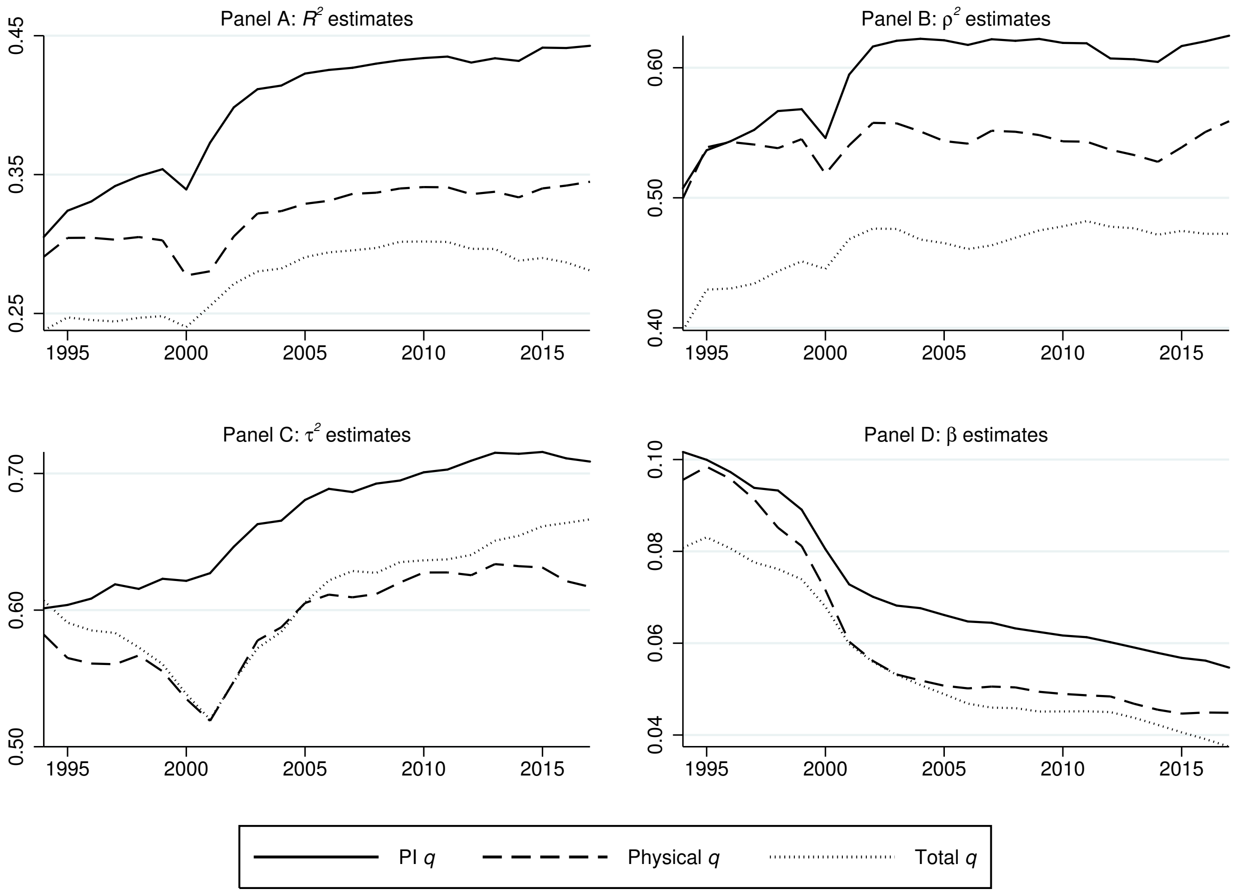

Figure 1.9. Total investment-*q* relation over time

This figure presents results from regressions of total investment on lagged q, firm fixed effects, and year fixed effects over 20-year rolling windows. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). Total investment is capital expenditures plus research and development expenses scaled by the denominator of lagged q being regressed on by investment. Panel A presents within R^2 estimates from OLS regressions, which are ordinary R^2 estimates from estimating OLS on the transformed data. Panel B presents ρ^2 estimates, which are within R^2 estimates from hypothetical regressions of total investment on marginal q. Panel C presents τ^2 estimates, which are within R^2 estimates from hypothetical regressions of q on marginal q. Panel D presents β estimates, which are bias-corrected coefficient estimates on q from cumulant estimator regressions of total investment on q. Each year represents the last year in the 20-year window.

Table 1.1. Summary statistics

This table presents estimates of different proxies for q and estimates of intangible capital for five different percentiles. Panels A and B present estimates of different proxies for q. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (i.e., book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). Panels C and D present estimates of patent capital, intangible capital, patent intensity, and intangible intensity. Patent capital and intangible capital are in millions of dollars. Patent intensity is patent capital divided by the sum of total capital, which is physical capital plus intangible capital. Intangible intensity is my estimate of intangible capital divided by total capital. Panels A and C present estimates for all firms. Panels B and D present estimates for firms with patent capital at any point during the sample.

Panel A: Estimates of q, all firms

	P10	P25	P50	P75	P90	Observations
PI q	-0.11	0.29	0.76	1.67	4.04	155,470
Physical q	-0.12	0.34	0.97	2.78	8.05	155,470
Total q	-0.06	0.20	0.58	1.22	2.54	155,470

Panel B: Estimates of q, firms with patent capital

	P10	P25	P50	P75	P90	Observations
PI q	-0.10	0.26	0.73	1.71	4.19	76,297
Physical q	-0.12	0.33	1.08	3.42	9.78	76,297
Total q	-0.06	0.18	0.55	1.22	2.56	76,297

Panel C: Estimates of intangible capital, all firms

	P10	P25	P50	P75	P90	Observations
Patent capital	0	0	0	4	148	155,470
Intangible capital	0	0	6	102	905	155,470
Patent intensity	0%	0%	0%	3%	26%	155,470
Intangible intensity	0%	0%	7%	34%	66%	155,470

Panel D: Estimates of intangible capital, firms with patent capital

	P10	P25	P50	P75	P90	Observations
Patent capital	0	0.2	4	75	904	76,297
Intangible capital	0.1	2	22	289	2,201	76,297
Patent intensity	0%	0%	3%	19%	51%	76,297
Intangible intensity	0%	3%	17%	47%	74%	76,297

Table 1.2. Investment and q: Ordinary least squares

This table presents results from ordinary least squares regressions of investment on lagged q, firm fixed effects, and year fixed effects. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). Physical investment is scaled capital expenditures. R&D investment is scaled research and development expenses. Total investment is physical investment plus R&D investment. All investment variables are scaled by the denominator of lagged q being regressed on by investment. Within R^2 estimates are ordinary R^2 estimates from estimating OLS on the transformed data. ΔR^2 is the R^2 estimate associated with PI q minus the R^2 estimate associated with either physical q (columns 2, 5, and 8) or total q (columns 3, 6, and 9) within each investment type. Panel A presents results for all firms. Panel B presents results for firms with patent capital at any point during the sample period. Standard errors in parentheses are clustered by firm. Standard errors below R^2 estimates and ΔR^2 estimates are estimated using influence functions. Bolded estimates are significant at the 5% level.

Panel A: All firms

	Physical investment			R&D investment			Total investment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PI q	**0.025**			**0.029**			**0.049**		
	(0.0004)			(0.0006)			(0.0008)		
Physical q		**0.015**			**0.020**			**0.032**	
		(0.0003)			(0.0005)			(0.0006)	
Total q			**0.029**			**0.015**			**0.034**
			(0.0005)			(0.0003)			(0.0006)
Within R^2	0.207	0.171	0.147	0.363	0.269	0.222	0.416	0.323	0.287
	(0.004)	(0.004)	(0.003)	(0.008)	(0.008)	(0.006)	(0.008)	(0.008)	(0.006)
ΔR^2	-	**0.036**	**0.060**	-	**0.094**	**0.142**	-	**0.093**	**0.129**
	-	(0.003)	(0.003)	-	(0.007)	(0.006)	-	(0.006)	(0.006)
Obs.	155,470	155,470	155,470	69,227	69,227	69,227	69,227	69,227	69,227

Panel B: Firms with patent capital

	Physical investment			R&D investment			Total investment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PI q	**0.020**			**0.033**			**0.054**		
	(0.0004)			(0.0007)			(0.0009)		
Physical q		**0.011**			**0.022**			**0.033**	
		(0.0003)			(0.0006)			(0.0008)	
Total q			**0.019**			**0.016**			**0.034**
			(0.0004)			(0.0004)			(0.0007)
Within R^2	0.268	0.199	0.176	0.378	0.272	0.229	0.431	0.323	0.292
	(0.006)	(0.005)	(0.004)	(0.009)	(0.009)	(0.007)	(0.009)	(0.009)	(0.006)
ΔR^2	-	**0.069**	**0.092**	-	**0.106**	**0.149**	-	**0.108**	**0.139**
	-	(0.005)	(0.004)	-	(0.008)	(0.007)	-	(0.008)	(0.007)
Obs.	76,297	76,297	76,297	53,855	53,855	53,855	53,855	53,855	53,855

Table 1.3. Investment and q: Cumulant estimator

This table presents results from cumulant estimator regressions of investment on lagged q, firm fixed effects, and year fixed effects. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). Physical investment is scaled capital expenditures. R&D investment is scaled research and development expenses. Total investment is physical investment plus R&D investment. All investment variables are scaled by the denominator of lagged q being regressed on by investment. ρ^2 is the within R^2 estimate from the hypothetical regression of investment on marginal q. τ^2 is the within R^2 estimate from the hypothetical regression of estimated q on marginal q. Panel A presents results for all firms. Panel B presents results for firms with patent capital at any point during the sample period. Standard errors in parentheses are estimated using influence functions and are clustered by firm. Bolded coefficients are significant at the 5% level.

Panel A: All firms

	Physical investment			R&D investment			Total investment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PI q	**0.046**			**0.047**			**0.072**		
	(0.0005)			(0.0008)			(0.0010)		
Physical q		**0.030**			**0.039**			**0.053**	
		(0.0004)			(0.0010)			(0.0110)	
Total q			**0.068**			**0.029**			**0.055**
			(0.0011)			(0.0006)			(0.0009)
ρ^2	0.387	0.347	0.347	0.585	0.515	0.430	0.607	0.533	0.466
	(0.009)	(0.010)	(0.010)	(0.017)	(0.020)	(0.015)	(0.015)	(0.017)	(0.014)
τ^2	0.534	0.492	0.423	0.621	0.522	0.516	0.686	0.606	0.615
	(0.011)	(0.012)	(0.011)	(0.019)	(0.022)	(0.018)	(0.016)	(0.020)	(0.017)
Obs.	155,470	155,470	155,470	69,227	69,227	69,227	69,227	69,227	69,227

Panel B: Firms with patent capital

	Physical investment			R&D investment			Total investment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PI q	**0.035**			**0.052**			**0.078**		
	(0.0005)			(0.0010)			(0.0011)		
Physical q		**0.021**			**0.041**			**0.054**	
		(0.0004)			(0.0014)			(0.0014)	
Total q			**0.040**			**0.030**			**0.054**
			(0.0008)			(0.0007)			(0.0010)
ρ^2	0.456	0.380	0.368	0.593	0.517	0.426	0.622	0.537	0.468
	(0.013)	(0.014)	(0.013)	(0.018)	(0.023)	(0.016)	(0.017)	(0.021)	(0.015)
τ^2	0.589	0.524	0.479	0.637	0.526	0.537	0.693	0.600	0.624
	(0.015)	(0.016)	(0.015)	(0.021)	(0.026)	(0.021)	(0.018)	(0.023)	(0.019)
Obs.	76,297	76,297	76,297	53,855	53,855	53,855	53,855	53,855	53,855

Table 1.4. Investment, *q*, and cash flow

This table presents results from cumulant estimator regressions of investment on lagged q, cash flow, firm fixed effects, and year fixed effects. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). Physical investment is scaled capital expenditures. R&D investment is scaled research and development expenses. Total investment is physical investment plus R&D investment. Cash flow is income before extraordinary items plus depreciation and amortization plus tax-adjusted R&D expenses. All regression variables are scaled by the denominator of lagged q being regressed on by investment. ρ^2 is the within R^2 estimate from the hypothetical regression of investment on marginal q. τ^2 is the within R^2 estimate from the hypothetical regression of estimated q on marginal q. Panel A presents results for all firms. Panel B presents results for firms with patent capital at any point during the sample period. Standard errors in parentheses are estimated using influence functions and are clustered by firm. Bolded coefficients are significant at the 5% level.

Panel A: All firms

	Physical investment			R&D investment			Total investment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PI q	**0.046**			**0.048**			**0.073**		
	(0.0007)			(0.0009)			(0.0010)		
Physical q		**0.029**			**0.039**			**0.054**	
		(0.0005)			(0.0011)			(0.0012)	
Total q			**0.067**			**0.031**			**0.056**
			(0.0013)			(0.0007)			(0.0010)
Cash flow	0.005	-0.001	-0.007	**-0.019**	**-0.026**	**-0.030**	**0.035**	0.004	**0.023**
	(0.005)	(0.004)	(0.007)	(0.008)	(0.008)	(0.005)	(0.011)	(0.010)	(0.009)
ρ^2	0.387	0.337	0.343	0.594	0.510	0.435	0.629	0.536	0.488
	(0.009)	(0.009)	(0.009)	(0.017)	(0.019)	(0.015)	(0.015)	(0.017)	(0.014)
τ^2	0.535	0.507	0.428	0.612	0.529	0.516	0.663	0.603	0.589
	(0.012)	(0.013)	(0.012)	(0.017)	(0.021)	(0.016)	(0.016)	(0.020)	(0.016)
Obs.	155,470	155,470	155,470	69,227	69,227	69,227	69,227	69,227	69,227

Table 1.4. continued

Panel B: Firms with patent capital

	Physical investment			R&D investment			Total investment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PI q	**0.034**			**0.054**			**0.079**		
	(0.0006)			(0.0010)			(0.0012)		
Physical q		**0.020**			**0.041**			**0.054**	
		(0.0004)			(0.0013)			(0.0014)	
Total q			**0.040**			**0.032**			**0.056**
			(0.0009)			(0.0008)			(0.0012)
Cash flow	**0.017**	**0.009**	0.008	**-0.023**	**-0.032**	**-0.033**	**0.042**	0.006	**0.030**
	(0.006)	(0.004)	(0.007)	(0.011)	(0.010)	(0.007)	(0.014)	(0.012)	(0.011)
ρ^2	0.468	0.373	0.373	0.607	0.508	0.435	0.654	0.538	0.497
	(0.013)	(0.013)	(0.012)	(0.018)	(0.022)	(0.017)	(0.016)	(0.019)	(0.015)
τ^2	0.575	0.534	0.472	0.623	0.537	0.532	0.661	0.599	0.588
	(0.016)	(0.018)	(0.016)	(0.019)	(0.024)	(0.019)	(0.017)	(0.022)	(0.018)
Obs.	76,297	76,297	76,297	53,855	53,855	53,855	53,855	53,855	53,855

Table 1.5. Investment, q, and cash flow: Correlations

This table presents correlations between investment, lagged q, and cash flow. All variables have been demeaned to account for firm fixed effects and year fixed effects. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). Physical investment is scaled capital expenditures. R&D investment is scaled research and development expenses. Total investment is physical investment plus R&D investment. Cash flow is income before extraordinary items plus depreciation and amortization plus tax-adjusted R&D expenses. All variables are scaled by the denominator of q unique to each correlation matrix. Panel A presents correlations for physical investment. Panel B presents correlations for R&D investment. Panel C presents correlations for total investment. Panel D presents bias-corrected cash flow coefficients and associated standard errors from Table 1.4. Bolded coefficients are significant at the 5% level.

Panel A: Physical investment

	Phys. inv.	PI q		Phys. inv.	Physical q		Phys. inv.	Total q
PI q	0.45	-	Physical q	0.41	-	Total q	0.38	-
Cash flow	0.30	0.35	Cash flow	0.23	0.29	Cash flow	0.25	0.29

Panel B: R&D investment

	R&D inv.	PI q		R&D inv.	Physical q		R&D inv.	Total q
PI q	0.60	-	Physical q	0.52	-	Total q	0.47	-
Cash flow	0.31	0.34	Cash flow	0.20	0.25	Cash flow	0.23	0.32

Panel C: Total investment

	Total inv.	PI q		Total inv.	Physical q		Total inv.	Total q
PI q	0.64	-	Physical q	0.57	-	Total q	0.54	-
Cash flow	0.36	0.34	Cash flow	0.24	0.25	Cash flow	0.31	0.32

Panel D: Cash flow coefficients

Physical investment			R&D investment			Total investment		
PI q	Physical q	Total q	PI q	Physical q	Total q	PI q	Physical q	Total q
0.005	-0.001	-0.007	**-0.019**	**-0.026**	**-0.030**	**0.035**	0.004	**0.023**
(0.005)	(0.004)	(0.007)	(0.008)	(0.008)	(0.005)	(0.011)	(0.010)	(0.009)

Table 1.6. Robustness: Changes to patent capital

This table presents results from regressions of investment on lagged PI q, firm fixed effects, and year fixed effects. The numerator of PI q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of PI q is physical capital (book value of gross property, plant, and equipment), plus the replacement cost of patent capital and on-balance sheet intangible capital. Physical investment is scaled capital expenditures. R&D investment is scaled research and development expenses. Total investment is physical investment plus R&D investment. All investment variables are scaled by the denominator of PI q. The dependent variable in the first, second, and third sets of columns is physical investment, R&D investment, and total investment. The first row of each panel presents the main results from Tables 1.2 and 1.3. The second through sixth rows of Panel A present results after making changes to the patent capital depreciation rate. The second through fifth rows of Panel B present results after making changes to the marginal q of new patents. The first column in each set of columns presents the bias-corrected coefficient on PI q. R^2 estimates are ordinary R^2 estimates from estimating OLS on the transformed data. ρ^2 is the within R^2 estimate from the hypothetical regression of investment on marginal q. τ^2 is the within R^2 estimate from the hypothetical regression of PI q on marginal q.

Panel A: Changes to the patent capital depreciation rate

	Physical investment				R&D investment				Total investment			
	β	R^2	ρ^2	τ^2	β	R^2	ρ^2	τ^2	β	R^2	ρ^2	τ^2
1. Main results (industry-specific δ_p)	0.046	0.207	0.387	0.534	0.047	0.363	0.585	0.621	0.072	0.416	0.607	0.686
2. δ_p of 15%	0.046	0.208	0.388	0.536	0.047	0.366	0.588	0.623	0.072	0.419	0.608	0.690
3. δ_p of 20%	0.046	0.207	0.387	0.534	0.047	0.363	0.585	0.620	0.072	0.416	0.606	0.686
4. δ_p of 25%	0.046	0.206	0.387	0.532	0.047	0.359	0.581	0.618	0.071	0.412	0.603	0.684
5. δ_p of 30%	0.046	0.205	0.387	0.529	0.047	0.356	0.577	0.616	0.071	0.409	0.600	0.682
6. Double industry-specific δ_p	0.046	0.204	0.386	0.528	0.047	0.349	0.572	0.611	0.071	0.404	0.599	0.675

Panel B: Changes to the marginal q of new patents

	Physical investment				R&D investment				Total investment			
	β	R^2	ρ^2	τ^2	β	R^2	ρ^2	τ^2	β	R^2	ρ^2	τ^2
1. Main results (marginal q of 1.50)	0.046	0.207	0.387	0.534	0.047	0.363	0.585	0.621	0.072	0.416	0.607	0.686
2. Marginal q of 1.00	0.047	0.210	0.389	0.541	0.047	0.375	0.593	0.633	0.072	0.428	0.614	0.697
3. Marginal q of 1.25	0.046	0.209	0.388	0.538	0.047	0.368	0.589	0.625	0.072	0.421	0.611	0.690
4. Marginal q of 1.75	0.046	0.206	0.386	0.532	0.047	0.359	0.582	0.617	0.071	0.412	0.604	0.682
5. Marginal q of 2.00	0.045	0.205	0.386	0.530	0.047	0.356	0.579	0.615	0.071	0.408	0.601	0.680

Table 1.7. Robustness: Higher-order cumulants

This table presents results from cumulant estimator regressions of investment on lagged q, firm fixed effects, and year fixed effects using higher-order cumulants. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). Physical investment is scaled capital expenditures. R&D investment is scaled research and development expenses. Total investment is physical investment plus R&D investment. All investment variables are scaled by the denominator of lagged q being regressed on by investment. The first column in each set of columns presents the bias-corrected coefficient on q. ρ^2 is the within R^2 estimate from the hypothetical regression of investment on marginal q. τ^2 is the within R^2 estimate from the hypothetical regression of the proxy for q on marginal q.

Panel A: Investment and PI q

	Physical investment			R&D investment			Total investment		
	β	ρ^2	τ^2	β	ρ^2	τ^2	β	ρ^2	τ^2
1. Main results (third-order)	0.046	0.387	0.534	0.047	0.585	0.621	0.072	0.607	0.686
2. Fourth-order	0.041	0.345	0.599	0.048	0.594	0.608	0.068	0.574	0.722
3. Fifth-order	0.042	0.350	0.590	0.048	0.596	0.606	0.068	0.572	0.725
4. Sixth-order	0.039	0.332	0.622	0.040	0.489	0.739	0.066	0.552	0.751
5. Seventh-order	0.041	0.347	0.594	0.047	0.579	0.623	0.068	0.569	0.728
6. Eighth-order	0.038	0.318	0.650	0.044	0.539	0.670	0.065	0.546	0.759

Panel B: Investment and physical q

	Physical investment			R&D investment			Total investment		
	β	ρ^2	τ^2	β	ρ^2	τ^2	β	ρ^2	τ^2
1. Main results (third-order)	0.030	0.347	0.492	0.039	0.515	0.522	0.053	0.533	0.606
2. Fourth-order	0.025	0.287	0.593	0.042	0.556	0.482	0.053	0.525	0.615
3. Fifth-order	0.025	0.290	0.588	0.040	0.526	0.509	0.052	0.521	0.618
4. Sixth-order	0.024	0.273	0.626	0.040	0.536	0.499	0.047	0.471	0.684
5. Seventh-order	0.025	0.289	0.590	0.037	0.492	0.545	0.052	0.522	0.618
6. Eighth-order	0.025	0.287	0.595	0.039	0.519	0.516	0.052	0.514	0.627

Table 1.7. continued

Panel C: Investment and total q

	Physical investment			R&D investment			Total investment		
	β	ρ^2	τ^2	β	ρ^2	τ^2	β	ρ^2	τ^2
1. Main results (third-order)	0.068	0.347	0.421	0.029	0.430	0.516	0.055	0.466	0.615
2. Fourth-order	0.083	0.230	0.344	0.030	0.449	0.493	0.051	0.432	0.663
3. Fifth-order	0.083	0.229	0.345	0.030	0.445	0.498	0.052	0.442	0.648
4. Sixth-order	0.183	0.509	0.155	0.028	0.418	0.531	0.047	0.400	0.715
5. Seventh-order	0.070	0.194	0.408	0.029	0.425	0.521	0.052	0.441	0.649
6. Eighth-order	0.160	0.444	0.178	0.026	0.390	0.568	0.056	0.477	0.600

Table 1.8. Robustness: Changes to intangible capital

This table presents results from regressions of investment on lagged PI q, firm fixed effects, and year fixed effects. The numerator of PI q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of PI q is physical capital (book value of gross property, plant, and equipment), plus the replacement cost of patent capital and on-balance sheet intangible capital. Physical investment is scaled capital expenditures. R&D investment is scaled research and development expenses. Total investment is physical investment plus R&D investment. All investment variables are scaled by the denominator of PI q. The dependent variable in the first, second, and third sets of columns is physical investment, R&D investment, and total investment. The first row of each panel presents the main results from Tables 1.2 and 1.3. The second and third rows of Panel A exclude the replacement cost of patent capital or on-balance sheet intangible capital. In Panel B, the second, third, and fourth rows add estimates of knowledge capital, organization capital, and knowledge capital plus organization capital from Peters and Taylor (2017). The fifth, sixth, and seventh rows of Panel B include estimates of knowledge capital, organization capital, and knowledge capital plus organization capital from Ewens et al. (2020). The first column in each set of columns presents the bias-corrected coefficient on PI q. R^2 estimates are ordinary R^2 estimates from estimating OLS on the transformed data (firm and year fixed effects). ρ^2 is the within R^2 estimate from the hypothetical regression of investment on marginal q. τ^2 is the within R^2 estimate from the hypothetical regression of PI q on marginal q.

Panel A: Changes to PI q

	Physical investment				R&D investment				Total investment			
	β	R^2	ρ^2	τ^2	β	R^2	ρ^2	τ^2	β	R^2	ρ^2	τ^2
1. Main results	0.046	0.207	0.387	0.534	0.047	0.363	0.585	0.621	0.072	0.416	0.607	0.686
2. Exclude patent capital	0.037	0.192	0.367	0.523	0.043	0.329	0.553	0.595	0.060	0.379	0.568	0.667
3. Exclude on-bs intangibles	0.037	0.191	0.369	0.518	0.042	0.318	0.551	0.577	0.062	0.374	0.569	0.657

Panel B: Changes to intangible capital

	Physical investment				R&D investment				Total investment			
	β	R^2	ρ^2	τ^2	β	R^2	ρ^2	τ^2	β	R^2	ρ^2	τ^2
1. Main results	0.046	0.207	0.387	0.534	0.047	0.363	0.585	0.621	0.072	0.416	0.607	0.686
2. Include know. capital (PT)	0.061	0.165	0.352	0.468	0.030	0.254	0.463	0.548	0.060	0.316	0.499	0.633
3. Include org. capital (PT)	0.058	0.175	0.372	0.471	0.051	0.317	0.577	0.550	0.076	0.378	0.594	0.636
4. Include know. plus org. capital (PT)	0.073	0.153	0.355	0.430	0.033	0.238	0.460	0.518	0.062	0.302	0.489	0.618
5. Include know. capital (EPW)	0.059	0.168	0.357	0.471	0.030	0.257	0.463	0.556	0.060	0.320	0.506	0.632
6. Include org. capital (EPW)	0.060	0.171	0.371	0.461	0.052	0.309	0.576	0.536	0.078	0.371	0.592	0.626
7. Include know. plus org. capital (EPW)	0.072	0.152	0.355	0.430	0.034	0.231	0.459	0.504	0.062	0.298	0.487	0.611

CHAPTER 2. SMALL INNOVATORS: NO RISK, NO REWARD

2.1 Introduction

Small, innovative firms tend to focus on the development of new products (Kraft, 1990; Cohen and Klepper, 1996; Klepper, 1996) and contribute disproportionately to major innovations (Rosen, 1991; Akcigit, 2009; Akcigit and Kerr, 2018). These "small innovators" have received significant attention for their contribution to creative destruction and economic growth (Klette and Kortum, 2004; Kung and Schmid, 2015; Acemoglu et al., 2018), the financial constraints they face (Himmelberg and Petersen, 1994; Carpenter and Petersen, 2002), and the role public equity plays in funding their growth (Brown et al., 2009; Acharya and Xu, 2017). However, there is little research that focuses on the cost of public equity for small innovators. In this paper, we therefore examine the risk and return of investing in publicly-traded small innovators.

Innovative firms might earn higher returns than non-innovative firms for two reasons. First, patents, which often protect innovation, are obtained in the early stages of the innovation process and have option-like characteristics (Pakes, 1986). Therefore, innovative firms likely have relatively large investment options, which might lead to higher risk because options amplify innovative firms' underlying systematic risk (Dixit and Pindyck, 1994; Berk et al., 1999). Thus, innovation can lead to return predictability even if investors correctly anticipate the long-term implications of patent announcements and trade until the associated information is fully incorporated into stock prices. Second, recently-issued patents may be difficult for investors to assess, which might lead to investor underreaction and higher future returns (Hirshleifer et al., 2013; Chemmanur et al., 2019).

Either explanation is especially applicable to small innovators. First, small innovators may rely disproportionately on patent assets, which would increase the systematic risk of firms. Second, the type of patents pursued by small innovators may have a larger effect on their systematic risk. For example, small innovators focus more on risky product innovation than on process innovation (Kraft, 1990; Cohen and Klepper, 1996; Klepper, 1996). Third, small firms rely more on organization capital (i.e., human capital), which increases systematic risk (Eisfeldt and Papanikolaou, 2013; Israelsen and Yonker, 2017). Since organization capital is important for both the resolution of real options (Kim and Kogut, 1996; Ziedonis, 2007) and the innovative process (Cohen and Levinthal, 1990), the effect of organization capital on systematic risk is likely higher for small innovators. Alternatively, underreaction to patent announcements might be more concentrated among small firms because analysts and other market participants produce noisier information about small firms (Brown et al., 1987).

To investigate these possibilities, we start by analyzing the returns of innovative firms, which we define based on the number of recently-granted patents, after sorting by firm size. Consistent with the above theories, we find that the return difference between innovative firms and non-innovative firms—which we call the innovative premium—is highest among small firms and decreases in firm size. For example, in the six months following portfolio formation, the equal-weighted innovative premium is 42 basis points per month in the three smallest NYSE size deciles (t-statistic of 3.72) and 52 basis points per month in the smallest NYSE size decile (t-statistic of 4.64). We obtain similar premiums across different holding period lengths and slightly lower, but always highly significant, value-weighted premiums among small firms. On the other hand, we do not find the innovative premium to be significant among large firms. The innovative premium among small firms is robust to adjustments for various risk factors, alternative thresholds for defining firms as innovative, and cannot be explained by stock characteristics. The premium is also not driven by microcap stocks, a group for which liquidity or other microstructure issues may be important. We obtain similar results using either the portfolio formation approach of Jegadeesh and Titman (1993, 2001) or the regression approach of Fama and MacBeth (1973).

As expected, innovative activity varies significantly across industries and over time. We find that the innovative premium among small firms is positive within most industries and higher within industries with more innovative firms, such as business equipment (i.e. computers, software, and electronic equipment). As a result, the innovative premium remains robust after adjusting for industry returns. We also find that the innovative premium is stronger in the latter half of our sample, which coincides with a substantial increase in patenting activity by small innovators.

To better understand the sources of the innovative premium among small firms, we perform a battery of tests that provides overwhelming support for a risk-based explanation. First, we find that small innovators earn higher returns than small non-innovators for up to five years. Long-term persistence in the innovative premium is difficult to reconcile with an underreaction-based explanation. Second, if underreaction is the source of return predictability, abnormal stock returns of small innovators should be positive and stable in the short-run (Bernard and Thomas, 1989). However, we find that the returns and fundamentals of small innovators are more volatile in both the short-run and long-run. Third, we test whether our results vary with investor attention, as proxied by IBES analyst coverage (Hirshleifer et al., 2013). Inconsistent with underreaction, we find that the returns of small innovators increase in analyst coverage. Finally, we compare the returns of persistent innovators to those of sporadic innovators. Assuming investors learn from past experiences, investors are less likely to underreact to patent announcements of persistent innovators. Contrary to underreaction, we find that persistent innovators earn significantly higher returns than sporadic innovators. Overall, we do not find any evidence supporting an underreaction-based explanation of our results.

All of the above findings, however, are consistent with a risk-based explanation. For example, persistent innovators may earn higher returns because they have more existing option-like assets. Indeed, we find that the returns of small innovators increase in the value of patent assets scaled by market capitalization (i.e., relative patent assets).

Next, we investigate why the innovative premium is present among small firms but not among large firms. Relative to large innovators, small innovators may have higher relative patent assets, focus on riskier patents, or rely more on risky organization capital. First, we find that average relative patent assets for large innovators are higher, not lower, than those for small innovators. We also find that unlike the returns of small innovators, the returns of large innovators do not increase in relative patent assets. If large innovators pursue low-risk innovations, their returns will not vary much with relative patent assets. Hence, it is possible that large innovators pursue innovations with low risk.

Accordingly, we test whether small innovators concentrate more on product innovation than on process innovation. Product innovation creates option-like assets that likely increase firms' systematic risk, while process innovation increases the value of existing assets through increased efficiency and productivity. Using data detailing claims types in patent grants (Bena and Simintzi, 2019), we find that small innovators focus more on product innovation and less on process innovation. Per granted patent, small innovators have more patent claims associated with product innovation (12.13 vs. 10.24) and fewer patent claims associated with process innovation (5.36 vs. 6.20) than large innovators. Furthermore, we find that the returns of small innovators, but not the returns of large innovators, increase in the number of product innovation claims.

Lastly, we check whether small innovators rely more on organization capital, which may amplify the risk of patents. To that end, we find that small innovators have more organization capital (32% vs. 22% of total assets) than large innovators. We also find that the returns of small innovators vary significantly with organization capital, but the returns of large innovators do not. We would not expect organization capital to generate significant variation in returns of large innovators if the underlying systematic risk of their patents is low.

In summary, our results indicate that small innovators are especially risky not because they have a higher share of relative patent assets than large innovators but because small innovators focus more on risky product innovation and rely more on organization capital than do large innovators.

The high returns of small innovators also meaningfully contribute to the size premium (Banz, 1981; Fama and French, 1992, 1993). We find that the size premium among innovative firms is 45 basis points per month, which is significantly higher than the size premium among non-innovative firms of 17 basis points per month. Given that the high returns of small innovators seem to be explained by the high risk associated with patents, our findings lend support to theories that explain the size premium through option-like assets (Carlson et al., 2004; Gârleanu et al., 2012).

Our paper is related to research that documents return predictability due to R&D investments (Lev and Sougiannis, 1999; Chan et al., 2001; Eberhart et al., 2004; Li, 2011; Cohen et al., 2013). We differ from this literature by focusing on innovative output (i.e., patents) and by studying a much larger sample by not restricting our sample to firms with non-missing R&D expenses. Among small innovators, R&D expenses are sparsely available. For example, if we used the innovative efficiency measure of Cohen et al. (2013), which uses historical R&D expenses as an input, we would lose 60% of our sample of small innovators.

There is also a closely-related literature that investigates return predictability based on patent citations, patent originality, innovative efficiency, and investor attention (Deng et al., 1999; Gu, 2005; Hirshleifer et al., 2013, 2017; Chemmanur et al., 2019). This literature provides evidence of return predictability due to mispricing. In contrast, we focus on a simple measure of innovation and small innovators, for which their fundamentally risky nature and the relatively high visibility of patent announcements result in return predictability due to risk.

Given the importance of innovation for economic growth, there is a large literature that focuses on the differences in incentives of innovative firms and their characteristics (Acs and

Audretsch, 1988; Klette and Kortum, 2004).[1] We contribute to this literature by providing direct evidence that investors consider small innovators to be risky, i.e., investors require higher returns for holding the equity of small innovators. Consequently, small innovators have a higher cost of equity, which potentially explains why small innovators rely heavily on internal capital.

2.2 Sample

All stock data are from the CRSP Monthly Stock file and include all ordinary common shares (share codes 10 through 12) that trade on NYSE, AMEX, NASDAQ, or ARCA. We exclude financials (SIC codes 6000-6799), utilities (SIC codes 4900-4949), and firms with missing SIC codes.[2] Accounting data are from the CRSP/Compustat Merged annual file. Due to the expansion of CRSP beginning July 2, 1962 and the robustness of accounting data in Compustat beginning in 1962, the sample spans July 1962 through December 2017. We follow Shumway (1997) in accounting for delisting returns. To avoid potential market microstructure issues, we eliminate observations that have a price of less than one dollar at the time of portfolio formation.

The patent database used in this paper is an extension of the one developed by Kogan et al. (2017), which spans 1926 to 2010. We extend the database through September 12, 2017 and add approximately 500,000 new patents during the period between 2010 and 2017. In the pre-2010 portion of the database, we add about 30,000 additional CRSP-matched patents to the Kogan et al. (2017) database by manually checking assignee names in almost 1.5 million patents. This manual check helps resolve issues associated with mergers, acquisitions, asset sales, spin-offs, and other sources of inconsistency.[3]

Table 2.1 presents summary statistics for innovative firms and non-innovative firms separately for small firms, medium firms, and large firms. Small firms are firms in the three

[1] See He and Tian (2018) for a comprehensive review.
[2] We use SIC codes (*siccd*) from CRSP.
[3] Patent data is publicly available here or through Noah Stoffman's website.

smallest NYSE size deciles, medium firms are firms in middle four NYSE size deciles, and large firms are firms in the largest three NYSE size deciles.[4] We define firms as innovative if they have been issued at least one patent in the preceding twelve months and non-innovative otherwise.

Market capitalization is price multiplied by shares outstanding (in 1983 dollars, millions). Book-to-market is book equity divided by market equity (Davis et al., 2000). Profitability is income before extraordinary items scaled by book equity (Hou et al., 2015). Asset growth is the percentage change in total assets over the previous two fiscal years (Cooper et al., 2008). Momentum is the cumulative raw return beginning twelve months ago through the month before last (Jegadeesh and Titman, 1993, 2001). Short-term reversal is the previous month's return (Jegadeesh, 1990; Lehmann, 1990). Illiquidity is the absolute stock return in the previous month divided by total dollar volume in the same month (Amihud, 2002). Idiosyncratic volatility is the standard deviation of residuals from a regression of daily stock returns in excess of the risk-free rate on daily market returns in excess of the risk-free rate over the previous twelve months (Ang et al., 2006). Skewness is the total skewness of daily stock returns over the previous twelve months. Stock issuance is the percentage change in split-adjusted shares outstanding in the previous twelve months (Ikenberry et al., 1995).

Table 2.1 shows that for all size groups, relative to non-innovative firms, innovative firms almost always have lower averages for all characteristics except for market capitalization. Return predictability associated with these characteristics does not provide a clear indication of whether innovative firms should earn higher future returns than non-innovative firms. Regardless, we keep these differences in mind and later control for firm-specific characteristics and return factors associated with these characteristics.

As one might expect, innovative activity varies significantly across industries. Figure 2.1 presents the industrial composition of small firms (Panel A), medium firms (Panel B), and large firms (Panel C). Percentages are presented for all firms within a size group and for

[4] We obtain NYSE breakpoints from Ken French's website.

innovative firms within a size group. Each panel shows that firms in business equipment, healthcare, and manufacturing are more likely to be innovative than firms in most other industries. For example, Panel A shows that firms in business equipment, healthcare, and manufacturing comprise about 47% of all small firms, but the same three industries comprise about 75% of all small innovators. In subsequent tests, we control for the possibility that any return differences between industries are driving return differences between small innovators and small non-innovators.

2.3 Main results

In this section, we investigate whether small innovators earn higher returns than small non-innovators.

2.3.1 Returns to innovation by size

To test how size affects the returns of innovative firms, we analyze future average monthly returns after sorting firms by size in Table 2.2. We follow Jegadeesh and Titman (1993, 2001) in presenting average portfolio returns, and all t-statistics are calculated using Newey and West (1987) adjusted standard errors using twelve lags.

Panel A, which presents value-weighted returns, shows that average monthly returns of innovative firms decrease monotonically in size. For example, over a twelve-month holding period, small, medium, and large innovators earn an average of 135, 121, and 90 basis points per month. In contrast, regardless of the holding period length, average monthly returns of non-innovative firms do not decrease monotonically in size.

For each holding period length, the third column in Panel A presents the innovative premium, which is the average return from a zero-investment portfolio that buys innovative firms and sells short non-innovative firms. Regardless of the holding period length, the value-weighted innovative premium among small firms is between 32 and 34 basis points per month, highly significant, twice that of medium firms, and between 27 and 29 basis points higher than that of large firms.

Panel B of Table 2.2 shows that among small firms, the equal-weighted innovative premium is between 41 and 43 basis points per month. In other words, even within size groups, smaller innovators outperform smaller non-innovators. Although size matters even within size groups, in unreported tests, we find that our results are not driven solely by microcap stocks (i.e., stocks in the smallest NYSE size decile).[5] Among small stocks that are not microcap stocks, the value-weighted and equal-weighted innovative premiums are 28 and 36 basis points per month in the year following portfolio formation.

Of particular interest is the substantially larger size premium among innovative firms than among non-innovative firms. The difference in size premiums is explained entirely by the high returns of small innovators. The size premium among innovative firms is 45 basis points per month in the year following portfolio formation. Conversely, the size premium among non-innovative firms is only 17 basis points per month. About 30% of all firm-month observations are defined as innovative, and as a result, the high returns of small innovators contribute significantly to the overall size premium.[6]

The results in Table 2.2 confirm that return differences between innovative firms and non-innovative firms are largest among small firms. Importantly, the innovative premium is driven in large part by small innovators earning higher returns, whereas small non-innovators earn returns close to the unconditional average return.[7]

[5]In September 2013, the SEC published a note stating that "a typical definition [of microcap stocks] would be companies with a market capitalization of less than $250 or $300 million." According to the NYSE breakpoint information from Ken French's website, the breakpoint for the smallest size decile in September 2013 is $359.55 million. Thus, we use the smallest NYSE size decile as our microcap cutoff.

[6]Since we drop financials, utilities, firms with missing SIC codes, and stocks that are priced under one dollar at the time of portfolio formation, our sample is slightly different from that of Fama and French (1993). In addition, we look at return differences between small firms and large firms without regard to book-to-market ratios.

[7]Table **??** in the internet appendix shows that the size premium among innovative firms is even larger when focusing on the returns of extreme NYSE size deciles.

2.3.2 Returns of small innovators: Alternative innovative criteria

In the previous table, we identify firms as innovative if they have received at least one patent in the past twelve months. Since large firms patent more often than small firms, this criterion may not be appropriate for large firms.

To mitigate any potential concerns that this choice of criterion is masking the presence of an innovative premium among larger firms, we present the innovative premium after using alternative criteria among both small firms and large firms in the internet appendix (Table B.2). Our alternative criteria include being issued at least one patent in the previous six months, one patent in the previous eighteen months, two patents in the previous twelve months, and five patents in the previous twelve months. As the criteria become stricter, the innovative premium among small firms increases, but the innovative premium among large firms is almost unchanged. In fact, even when we increase the threshold for large firms to at least 25 patents or 50 patents in the previous twelve months, we see almost no change in the innovative premium.[8] Thus, our results are robust to using alternative criteria to identify innovative firms.

2.3.3 Factor model-adjusted returns

Next, we test whether the premium earned by small innovators is due to known risk factors. Table 2.3 presents the raw innovative premium, the innovative premium after adjusting for commonly-used risk factors, and factor loadings.

Panel A of Table 2.3 presents returns from value-weighted portfolios. The first row shows the raw innovative premium among small firms, which reproduces results from the first row in Panel A of Table 2.2. CAPM alphas, which are average monthly alphas from regressing the raw returns of the zero-investment portfolio on excess market returns, are between 28 and 30 basis points per month. Average FF3 alphas, which are average monthly alphas from

[8] We do not increase the criterion to at least 25 patents or 50 patents for small firms because there are not enough small firms to form portfolios every month using these two criteria.

regressing the raw returns of the zero-investment portfolio on the Fama and French (1993) three-factor model, are slightly higher than CAPM alphas. In the next two rows, we add a momentum factor (Carhart, 1997) or a liquidity factor (Pástor and Stambaugh, 2003) to the three-factor model, and the resulting alphas are similar to FF3 alphas. Lastly, we add a profitability factor and an investment factor (Fama and French, 2015) to the three-factor model, and the resulting FF5 alphas increase to between 42 and 44 basis points per month, which are higher than alphas associated with any other factor model.

Panel B of Table 2.3 shows that all of our results are slightly higher in equal-weighted portfolios. Corresponding t-statistics are all well above 3.00, which is the statistical hurdle suggested by Harvey et al. (2016) to address data mining issues.

In Panel C, we present the factor loadings from regressions of the value-weighted innovative premium on the Fama and French (2015) five-factor model. The factor loading for the market factor is close to zero and statistically insignificant for each holding period length. Although both the long and short legs of the zero-investment portfolio are comprised of small firms, the raw innovative premium still loads positively on the size factor (SMB). Loadings for the book-to-market (HML) and profitability (RMW) factors are negative, statistically significant, and consistent with differences in the corresponding characteristics in Table 2.1. Panel D shows that with the exception of the market factor loading, factor loadings are similar for equal-weighted portfolios. The innovative premium loads positively and significantly on the market factor in equal-weighted returns.

Overall, the results in Table 2.3 show that the innovative premium among small firms is not explained by known risk factors. In the rest of the paper, we focus on value-weighted portfolios, for they are relatively easier to invest in and produce a more conservative innovative premium.

2.3.4 Within-industry and industry-adjusted returns

As discussed above, Figure 2.1 shows that the propensity to innovate differs across industries. To understand how these differences manifest themselves in the innovative premium among small firms, we estimate within-industry and industry-adjusted innovative premiums in Table 2.4.

In Panel A, we present returns of small innovators, returns of small non-innovators, and the innovative premium among small firms within ten Fama-French industries (as before, utilities and financials are excluded).[9] The innovative premium is significantly positive in business equipment (i.e., computers, software, electronic equipment), consumer durables, consumer non-durables, and manufacturing industries. The premium is also positive, albeit insignificantly so, in chemicals, energy, healthcare, and other industries. Overall, within the majority of industries, the innovative premium is positive, and differences in the innovative premium across industries are mostly consistent with our priors. For example, the premium is largest in business equipment, in which there are many small innovators, but the premium is insignificant in both shops and telecoms, in which there are few small innovators.

Given that the innovative premium is positive in most industries and higher in industries with more innovative firms, we do not expect cross-industry differences in returns to explain our results. Regardless, we test whether the innovative premium survives adjustments for industry returns in Panel B of Table 2.4. An advantage of this test is that it allows us to control for cross-industry differences in returns at finer industry classifications without dropping any time periods. We present industry-adjusted innovative premiums and associated five-factor alphas for the Fama-French 12, 30, and 48 (FF12, FF30, FF48) industry classifications and SIC two-digit and three-digit (SIC2, SIC3) codes. The results in the first five columns show that regardless of the industry classification, the industry-adjusted innovative premium is between 26 and 34 basis points per month, which is similar to our main

[9] We require a minimum of five small innovators and five small non-innovators in a given month to form a portfolio. The small number of industries reduces the time periods with missing observations.

results. All associated t-statistics are above 3.00. The latter five columns show that our industry-adjusted results are also robust to controlling for the five-factor model.

The results in Table 2.4 show that the innovative premium among small firms is especially strong in industries with more small innovators and not driven by return differences across industries.

2.3.5 Subperiod analysis

In addition to significant inter-industry variation in innovation, there is also significant time-series variation in innovation. Figure 2.2 shows that patents granted to small firms began growing significantly around 1990. The time trend in innovative activity (i.e., patenting) of small firms might be driven by several factors, which include changes to the enforcement of patents (Hall, 2004) and the availability of public funding for young and innovative firms (Brown et al., 2009).

We test whether changes in innovative activity over time coincide with changes in the innovative premium among small firms. We evaluate raw returns and five-factor alphas over two roughly equal-sized periods and present the results in Table 2.5. Panel A presents raw returns from holding periods between July 1963 and December 1990. The innovative premium during this period is between 18 and 19 basis points per month, which is smaller than the innovative premium in the full sample. Panel B shows that after adjusting for commonly-used risk factors, the innovative premium during this period declines. Panels C and D of Table 2.5 present results from holding periods between January 1991 and December 2017. Panel C shows that the raw innovative premium during this period is between 46 and 48 basis points per month, and Panel D shows that average five-factor alphas are between 58 and 60 basis points per month. Similar patterns can also be observed in Figure 2.3, which plots the innovative premium over time.[10] Increases in the innovative premium in the second

[10] Figure 2.3 shows that average raw returns in the year 2000 are over 4% per month. However, our results are robust to removing the year 2000 from the sample. When excluding those returns from the 1991 through 2017 period, the average innovative premium is 31 basis points (t-statistic of 2.24) per month.

half of the sample are driven primarily by the higher returns of small innovators rather than the lower returns of small non-innovators.

In summary, Figure 2.2 and Table 2.5 show that the increase in patenting by small firms coincides with a higher premium to small innovators.

2.3.6 Fama-MacBeth regressions

In Table 2.6, we continue to focus on small firms and test whether small innovators earn higher returns in the cross-section after controlling for standard firm-level characteristics. The dependent variable in all specifications is future one-month returns. All non-dummy, independent variables are winsorized at the 1% and 99% levels each month and are standardized to mean zero and unit standard deviation. We present time-series averages of coefficient estimates from monthly cross-sectional regressions (Fama and MacBeth, 1973). As before, we calculate t-statistics using Newey and West (1987) adjusted standard errors using twelve lags.

In the first column of Table 2.6, the coefficient on innovative, which is a dummy that equals one if the firm has been issued at least one patent in the preceding twelve months and zero otherwise, is a highly significant 0.44 (t-statistic of 3.68). Thus, we estimate that small innovators earn 44 more basis points per month than small non-innovators.

We control for firm-level characteristics that are commonly used in factor models (i.e., natural log of book-to-market, profitability, asset growth, and momentum) in the second column. The inclusion of these controls decreases the coefficient on innovative a bit, but the coefficient is still 0.37 (t-statistic of 3.93), which is highly significant.

The third column includes additional controls known to predict future returns (i.e., short-term reversal, illiquidity, idiosyncratic volatility, skewness, and stock issuance). After including these controls, the coefficient on innovative is 0.34 (t-statistic of 3.54), which is hardly changed from that in the second column.

The fourth column includes all of the aforementioned control variables and industry (FF48) fixed effects. Consistent with our earlier results, the inclusion of industry fixed effects in the cross-section does not account for small innovators' relative outperformance.[11]

Overall, the results in Table 2.6 show that after controlling for a number of firm-level characteristics, small innovators earn significantly higher future one-month returns than small non-innovators.

2.4 Risk or underreaction?

In the previous section, we conclude that small innovators earn higher future returns than small non-innovators. These higher returns are robust to controlling for a number of variables known to predict returns. In this section, we conduct a battery of tests to ascertain whether our results are due to risk or underreaction. Each of these tests provides evidence that the innovative premium among small firms is driven by risk.

2.4.1 Long-run returns

To disentangle risk-based and underreaction-based explanations, we first compare long-run returns of small innovators to those of small non-innovators. If our results are driven by underreaction, we do not expect to see differences in long-run returns between the two groups of firms.

Table 2.7 presents long-run returns up to five years for both small innovators and small non-innovators. Panel A shows that the raw innovative premium is positive for each of the first five years after portfolio formation. Panel B shows that after adjusting for commonly-used risk factors, both innovative premiums and the returns of small innovators are positive and significant for each of the first five years after portfolio formation. These results show

[11]In unreported tests, we find that results are similar when using other industry classifications to control for industry fixed effects.

that small innovators earn higher returns than small non-innovators in the long-run, which makes it less likely that our results are explained by underreaction.

2.4.2 Volatilities of returns and fundamentals

Second, we analyze small innovators' short-run and long-run volatilities of returns and fundamentals. A risk-based explanation predicts higher volatilities of returns and fundamentals in both the short-run and long-run. In contrast, if underreaction is the source of return predictability, abnormal stock returns of small innovators should be mostly positive and relatively stable in the short-run (Bernard and Thomas, 1989).

Panels C and D of Table 2.7 present volatilities of raw returns and five-factor alphas in the five years following portfolio formation. Both panels show that regardless of the horizon, return volatilities are higher for portfolios of small innovators than they are for portfolios of small non-innovators. The p-values, which are from F-tests for equality of standard deviations, indicate that differences in volatilities are highly significant.

The higher return volatilities associated with small innovators are not without reward though. In unreported tests, we find that the monthly Sharpe ratio over the twelve-month holding period for the portfolio of small innovators is 0.136, which is 37% higher than the Sharpe ratio of 0.099 for the portfolio of small non-innovators.

In Table 2.8, we investigate long-term volatilities of firm-level fundamentals, which include cash flows (Panel A), net income (Panel B), earnings per share (Panel C), return on assets (Panel D), and return on equity (Panel E). Due to the skewness of these firm-level volatilities, we present volatilities for five different percentiles rather than just volatility means or medians.

Results are largely consistent across the five panels of Table 2.8; small innovators experience higher cash flow, earnings, and profitability volatilities than small non-innovators. Differences between the volatilities of small innovators and small non-innovators within each percentile and across risk proxies are consistently positive. In unreported Wilcoxon rank-sum and nonparametric equality-of-medians tests, we find that in each panel, volatilities of small innovators are significantly higher at the 1% level than volatilities of small non-innovators.

To the extent that return, cash flow, earnings, and profitability volatilities are proxies for risk, the results in the last two panels of Table 2.7 and in all panels of Table 2.8 are consistent with a risk-based explanation for the higher returns of small innovators.

2.4.3 Investor attention and returns

Third, we test whether the returns of small innovators vary with investor attention. Investors are more likely to underreact to patent announcements of innovative firms that have less analyst coverage (Hirshleifer and Teoh, 2003). To test whether returns vary with analyst coverage, we sort small innovators by the number of IBES earnings estimates over the previous twelve months and present the results in Table 2.9.

Small innovators without any earnings estimates over the previous twelve months fall into the no IBES group. Small innovators with at least one earnings estimate in the previous twelve months are sorted into IBES estimate groups based on breakpoints for the bottom 30% (lowest), middle 40% (mid), and top 30% (highest). Panel A shows that contrary to the investor inattention hypothesis, small innovators with more, not less, analyst attention earn higher returns. Return differences between no IBES and highest IBES groups are between -49 and -57 basis points. Panel B shows that five-factor alphas are also higher for small innovators with more analyst coverage. Overall, Table 2.9 shows that variation in the returns of small innovators is not explained by investor inattention.

2.4.4 Innovative persistence and returns

Lastly, we investigate the return difference between small innovators that innovate persistently and those whose patenting activity is more sporadic. Under the simple assumption that investors learn from past experiences, investors are less likely to underreact to patent announcements of firms that have consistently announced patents in the past. If our results are driven by underreaction, returns should be higher for less persistent innovators. On the other hand, a risk-based explanation implies that firms with more persistent innovation earn higher returns either because these firms are likely to have accumulated more option-like assets, which we test directly below, or because investors recognize the option value of future innovations of persistent innovators (Kung and Schmid, 2015).

We measure innovative persistence by the number of months a firm has been issued at least one patent between five years ago and one year ago. Small innovators with zero issued patents during the four-year period are sporadic innovators. Small innovators with at least one issued patent during the four-year period are sorted into persistence groups based on breakpoints for the bottom 30% (least), middle 40% (mid), and top 30% (most). We present the results in Table 2.10.

Panel A presents raw returns. For each holding period length, returns increase monotonically in the level of innovative persistence. Return differences between the most sporadic innovators and the most persistent innovators are between 39 and 47 basis points per month. Panel B shows that alphas also increase monotonically in investor persistence. For example, relative to sporadic innovators, the most persistent innovators earn higher alphas of between 30 and 43 basis points per month.

The results in Table 2.10 show that persistent innovators earn higher returns than less persistent innovators. These results provide support for a risk-based, rather than an underreaction-based, explanation of our results.

2.5 Why are small innovators riskier?

Each test in the previous section shows that small innovators earn higher returns than small non-innovators because small innovators are riskier. However, those tests do not provide evidence as to why there is an innovative premium among small firms but not among large firms. We consider three prominent examples. First, small innovators may rely more on patent assets. Second, small innovators may pursue riskier patents. Finally, small innovators may rely more on organization capital, which amplifies their systematic risk.

2.5.1 Relative patent assets and returns

Small innovators might rely disproportionality on patent assets, so obtaining additional patents, which are option-like in nature (Pakes, 1986), might increase the systematic risk of small innovators. On the other hand, large innovators may have considerable levels of other assets, so obtaining additional patents may not significantly change their systematic risk, if at all. To test these possibilities, we sort small innovators and large innovators by their relative amount of patent assets.

As in Kogan et al. (2017), we estimate patent values using the market reaction to patent announcements. However, we modify their methodology slightly to ensure that no future information is used in the estimation. This is important for our study given that we focus on return predictability.[12] We then estimate patent assets by accumulating estimated patent values using the perpetual inventory method:

$$A_{i,t} = (1 - \delta_P)A_{i,t-1} + P_{i,t}, \tag{2.1}$$

in which i indexes firms, t indexes months, A is patent assets, δ_P is the industry-specific depreciation rate, and P is the estimated value of new patents.[13] R&D is closely related to subsequently-granted patents, so we use industry-specific depreciation rates for R&D capital

[12] Details regarding the estimation of patent values can be found in the Online Appendix

[13] Although our sample begins in July 1962, we have estimated patent values back to 1926. In other words, provided that an innovator is granted a patent before our sample begins, patent assets begin accumulating before July 1962.

from Table 4 of Li (2012) to depreciate patent assets.[14] We accumulate and depreciate patent values on a monthly basis.

In Table 2.11, we present average future returns after sorting innovators into three relative patent assets groups based on breakpoints for the bottom 30% (lowest), middle 40% (mid), and top 30% (highest). We define relative patent assets as patent assets divided by market capitalization. Panel A shows that small innovators with the highest relative patent assets earn between 25 and 27 more basis points per month than small innovators with the lowest relative patent assets. Conversely, the returns of large innovators increase only slightly in relative patent assets, and return differences between large innovators with the highest and lowest relative patent assets are insignificant.

Panel B of Table 2.11 presents five-factor alphas. Small innovators in the highest group earn at least 19 more basis points per month than small innovators in the lowest two groups. However, among large innovators, alphas are similar across relative patent asset groups.

In unreported tests, we find that average relative patent assets are lower for small innovators than for large innovators. Thus, differences in the innovative premium between small firms and large firms are not explained by differences in relative patent assets. However, Table 2.11 shows that among small innovators, future returns increase in relative patent assets. These results suggest that patent assets increase the systematic risk of small innovators more than that of large innovators. This interpretation is consistent with small innovators pursuing riskier patents or patents having a larger impact on the systematic risk of small innovators.

[14]The average industry-specific depreciation rate is 25% and ranges from 10% (pharmaceuticals) to 40% (computers and peripheral equipment). If the industry is not explicitly listed, we follow guidelines set by the Bureau of Economic Analysis (BEA) and use an annual rate of 15%. We find that our results are insensitive to alternative patent depreciation rates of 15%, 20%, 25%, and 30%.

2.5.2 Product innovation and returns

Innovation type is known to vary with firm size. As firms grow, they can spread both the costs and benefits of innovation over larger levels of output, which increases the share of process innovation relative to risky product innovation (Kraft, 1990; Cohen and Klepper, 1996; Klepper, 1996). Process innovation refers to an improvement in one's own production methods, and product innovation refers to new products that are sold to others (Scherer, 1982). While process innovation increases the value of existing assets through increased efficiency and productivity, process innovation likely does not create the option-like assets associated with product innovation that increase the systematic risk of the firm.

The returns of small innovators might vary with patent assets because small innovators focus more on product innovation than large innovators. To test this prediction, we investigate how future returns vary with product innovation among both small innovators and large innovators.

We measure product innovation using data from textual analysis of patent claims (Bena and Simintzi, 2019). Patent claims define the scope of patent protection, and since claims are written in a legalistic way, they lend themselves to textual analysis. To that end, Bena and Simintzi (2019) use textual analysis to identify each patent claim as either a process claim or a non-process (i.e., product) claim. They conduct this analysis on over four million patents granted between January 1976 and December 2012.[15]

Table 2.12 presents future average returns after separately sorting small innovators and large innovators by product innovation. We measure product innovation by the raw number of product innovation claims in the previous twelve months and again sort groups based on breakpoints for the bottom 30% (fewest), middle 40% (mid), and top 30% (most). Panel A shows that there is significant variation in returns among small innovators but not among large innovators. For example, small innovators with the most product innovation claims

[15]Complete details of their methodology can be found in Appendix A of Bena and Simintzi (2019). We thank the authors for sharing their data.

earn between 30 and 31 more basis points per month than small innovators with the fewest product innovation claims. However, large innovators with the most product claims earn similar returns to those with the fewest product innovation claims. Panel B shows that variation in alphas follow a similar pattern among both small innovators and large innovators.

In unreported tests, we find that per granted patent, small innovators have more patent claims associated with product innovation and fewer patent claims associated with process innovation than large innovators. Consistent with our predictions, our unreported tests reveal that small innovators focus on relatively more product innovation, and the results in Table 2.12 show that small innovators with more product claims earn higher returns. Thus, some of the differences in innovative premiums between small firms and large firms seem to be due to the type of innovation in which these firms engage.

2.5.3 Organization capital and returns

Organization capital often refers to intangible capital embodied in the firm's key employees. Since key employees may leave the firm when the value of their outside options increases, organization capital may affect the firm's systematic risk. In particular, Eisfeldt and Papanikolaou (2013) and Israelsen and Yonker (2017) show that organization capital increases the firm's systematic risk and returns. Organization capital is especially critical for firms with real options, such as firms with patents (Kim and Kogut, 1996; Ziedonis, 2007). Therefore, organization capital may further amplify the systematic risk of small innovators.

To test this supposition, we present future average returns after sorting firms by organization capital in Table 2.13. Organization capital is estimated by cumulating 30% of firms' selling, general, and administrative (SG&A) expenses using the perpetual inventory method (Eisfeldt and Papanikolaou, 2014; Peters and Taylor, 2017). Using breakpoints for the bottom 30% (lowest), middle 40% (mid), and top 30% (highest), we sort firms based on their ratio of organization capital to book assets. Since the accounting treatment of

SG&A expenses varies across industries, we also sort within FF48 industries (Eisfeldt and Papanikolaou, 2013).

Panel A of Table 2.13 presents raw returns after sorting firms by organization capital. The first three columns show that the returns of small innovators increase significantly in organization capital. For example, small innovators in the highest group earn up to 51 more basis points per month than small innovators in the lowest group. The second three columns show that small non-innovators in the highest group earn up to 33 more basis points per month than small non-innovators in the lowest group. Consistent with Eisfeldt and Papanikolaou (2013), the returns of all small firms increase in organization capital. However, returns vary more among small innovators, which indicates that organization capital is more important for determining their risk.

Conversely, the third and fourth sets of columns in Panel A show that after sorting by organization capital, there is almost no variation in the returns of large innovators and large non-innovators. Among both groups, firms in the highest group earn only slightly more than firms in the lowest group. Panel B shows that five-factor alphas exhibit mostly the same patterns of return variation across small firms and large firms.

In unreported tests, we find that small innovators have more organization capital than large innovators. The results in Table 2.13 show that return variation is largest among small innovators. Taken together, these results support our argument that patents may increase the systematic risk of small innovators because small innovators rely more on organization capital that is important for the resolution of uncertainty associated with patents.

Overall, the results in Section 2.5 indicate that small innovators are riskier than large innovators because small innovators focus more on risky product innovation and rely more on organization capital.

2.6 Conclusion

In this paper, we analyze the risk and return of small, innovative firms. We document that small innovators earn significantly higher returns than small non-innovators. The innovative premium among small firms is robust to controlling for well-known stock characteristics, industry composition, lasts for up to five years, is not explained by investor inattention, and is driven by firms that are persistently innovative, have relatively more patent assets, focus more on risky innovation, and depend more on organization capital. Small innovators also have higher volatilities of returns and fundamentals than small non-innovators. Conversely, there is no such innovative premium among large firms. Relative to large innovators, small innovators focus more on product innovation and rely more on organization capital, which in turn increases the systematic risk of small innovators. Overall, small innovators have higher returns because they have higher risk.

We contribute to the broader literature on innovative firms by showing that small innovators have a higher cost of equity. Due to their lack of collateral and risky fundamentals, small innovators have poor access to debt markets (Himmelberg and Petersen, 1994; Carpenter and Petersen, 2002). Taken together, these results might explain why publicly-traded small innovators rely heavily on internal capital.

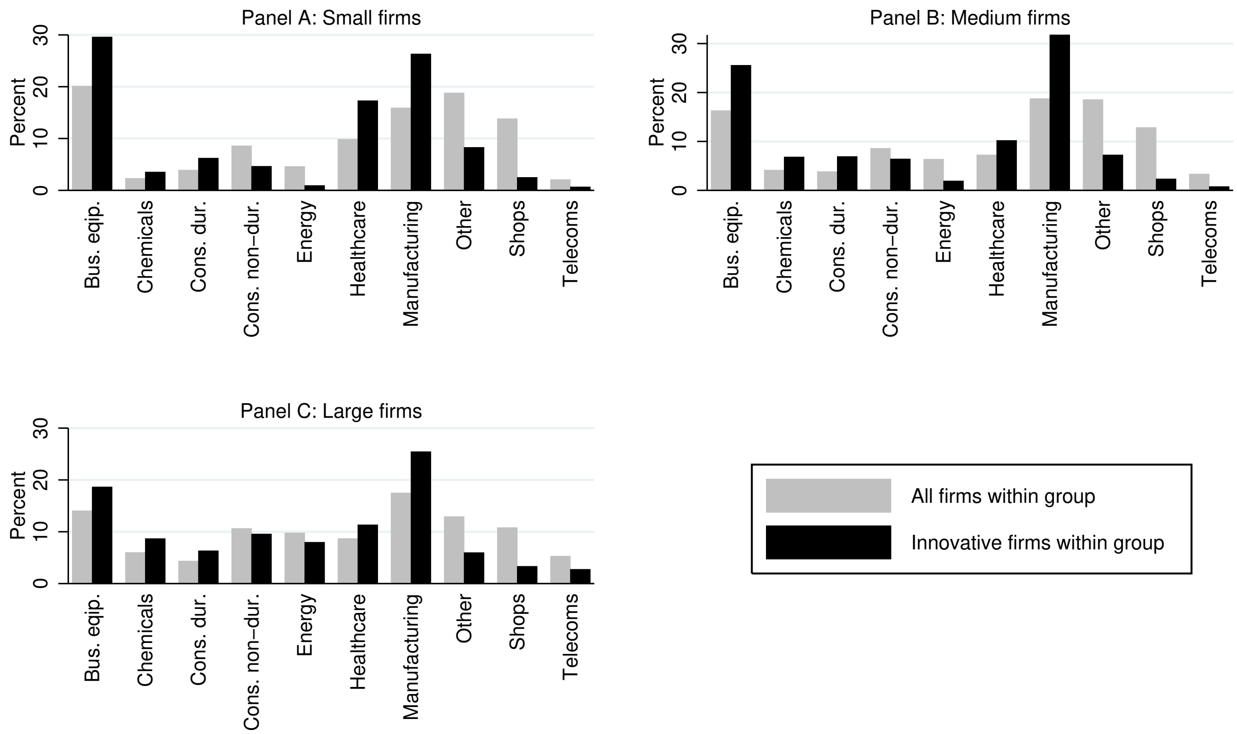

Figure 2.1. Innovative firms by industry and size

This figure presents the industrial composition of firms across ten Fama-French industries (financials and utilities excluded) within size groups. Small firms are firms in the three smallest NYSE size deciles, medium firms are firms in the middle four NYSE size deciles, and large firms are firms in the largest three NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months. Panel A presents percentages for small firms. Panel B presents percentages for medium firms. Panel C presents percentages for large firms.

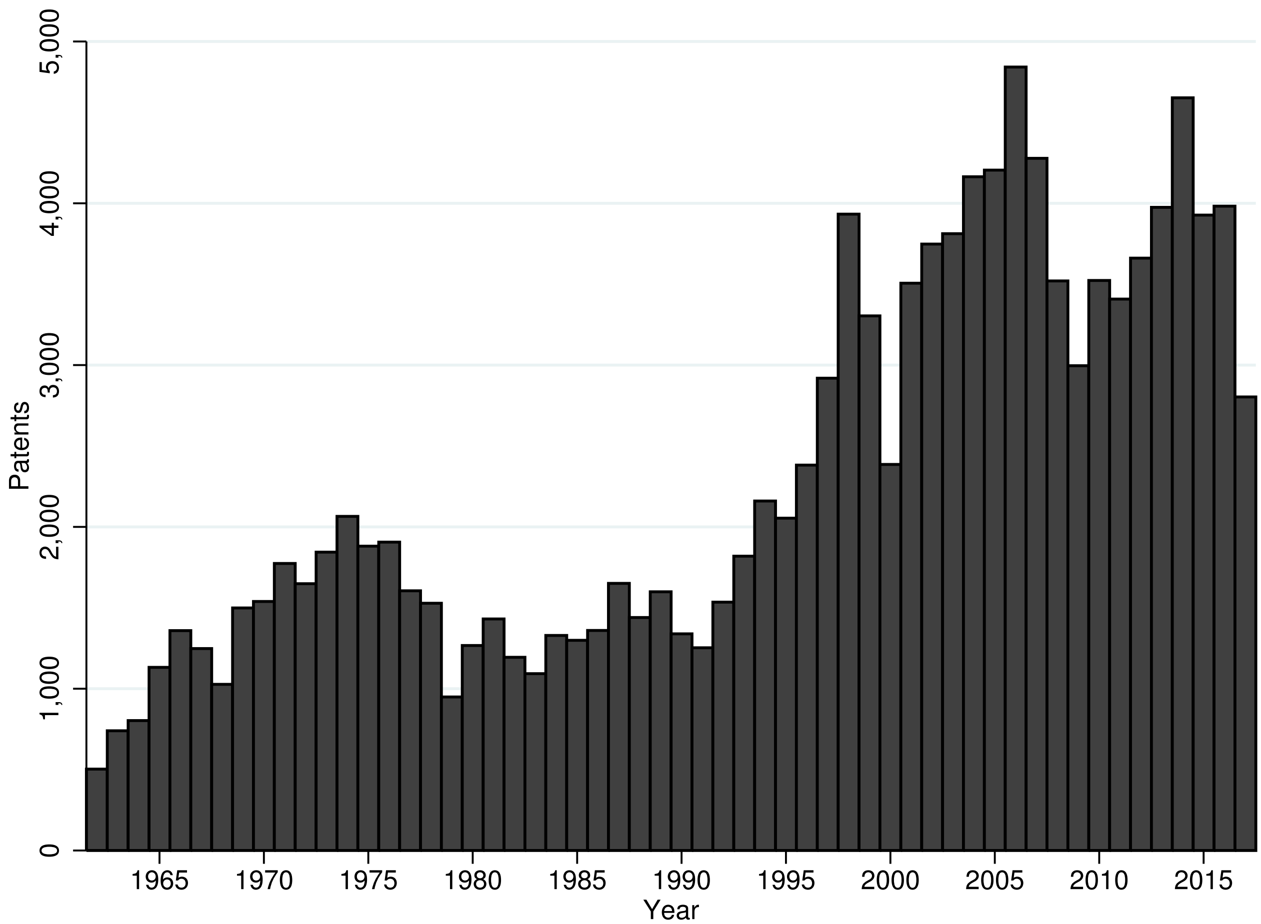

Figure 2.2. Annual patent totals of small firms

This figure presents the annual sum of patents issued to small firms. Small firms are firms in the three smallest NYSE size deciles. Since our data end on September 12, 2017, the 2017 patent total reflects that truncation.

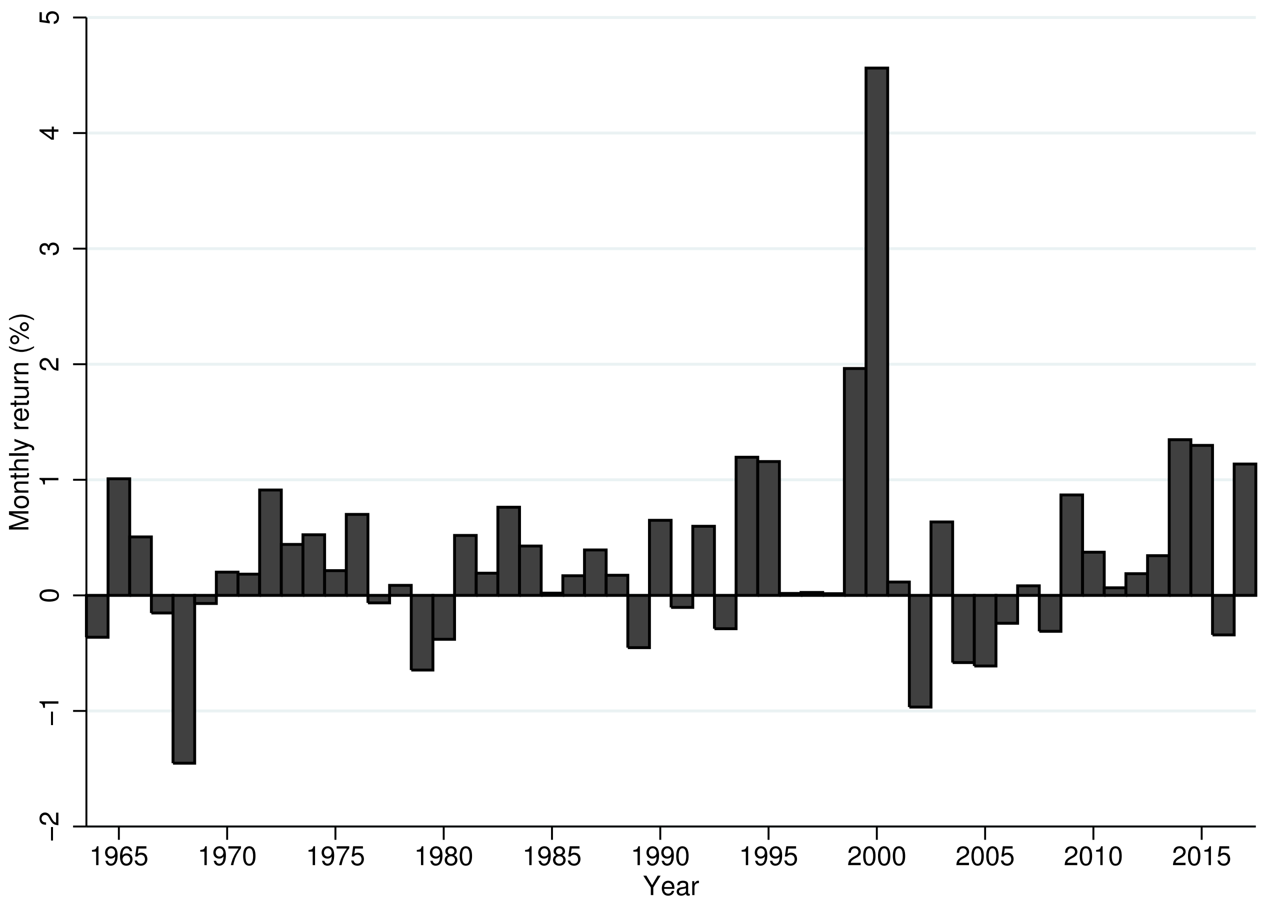

Figure 2.3. Average monthly innovative premium among small firms

This figure presents the average value-weighted innovative premium (twelve-month holding period) among small firms by year. Small firms are firms in the three smallest NYSE size deciles. The innovative premium is the return from buying firms with at least one issued patent in the preceding twelve months and selling short all other firms.

Table 2.1. Summary statistics

This table presents average firm-level characteristics after sorting firms by size. Averages are time-series averages of cross-sectional averages. Small firms are firms in the three smallest NYSE size deciles, medium firms are firms in the middle four NYSE size deciles, and large firms are firms in the largest three NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months and non-innovative otherwise. Market capitalization is price multiplied by shares outstanding (in 1983 dollars, millions). Book-to-market is book equity divided by market capitalization. Profitability is income before extraordinary items scaled by book equity. Asset growth is the percentage change in total assets over the last two fiscal years. Momentum is the cumulative raw return beginning twelve months ago through the month before last. Short-term reversal is the previous month's raw return. Illiquidity is the absolute stock return in the previous month divided by total dollar volume in the same month. Idiosyncratic volatility is the standard deviation of residuals from a regression of daily stock returns in excess of the risk-free rate on daily market returns in excess of the risk-free rate over the previous twelve months. Skewness is the total skewness of daily stock returns over the previous twelve months. Stock issuance is the percentage change in split-adjusted shares outstanding in the previous twelve months. Besides market capitalization, all variables are winsorized at the 1% and 99% levels each month.

	Small firms		Medium firms		Large firms	
	Innovative	Non-innovative	Innovative	Non-innovative	Innovative	Non-innovative
Monthly observations	491	1,867	282	467	241	150
Market capitalization	81	62	573	524	8,644	3,710
Book-to-market	0.89	0.99	0.69	0.66	0.56	0.58
Profitability	-10.08%	-3.82%	6.55%	10.13%	13.99%	13.45%
Asset growth	12.59%	14.78%	16.55%	20.93%	14.47%	19.11%
Momentum	10.61%	12.90%	20.39%	24.05%	18.35%	22.57%
Short-term reversal	1.06%	1.08%	1.81%	2.03%	1.55%	1.86%
Illiquidity	0.30	0.60	0.019	0.036	0.003	0.017
Idiosyncratic volatility	3.51%	3.73%	2.30%	2.35%	1.68%	1.82%
Skewness	0.65	0.74	0.36	0.39	0.20	0.25
Stock issuance	5.31%	5.86%	3.60%	5.02%	2.07%	3.82%

Table 2.2. Returns to innovation by size

This table presents future average monthly returns of innovative firms and non-innovative firms after sorting firms by size. Small firms are firms in the three smallest NYSE size deciles, medium firms are firms in the middle four NYSE size deciles, and large firms are firms in the largest three NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months and non-innovative otherwise. The innovative premium is the return from buying innovative firms and selling short non-innovative firms. Panel A presents results from value-weighted portfolios, and Panel B presents results from equal-weighted portfolios. Portfolios are formed at the end of every month between June 1963 and November 2017 and held for either three, six, or twelve months. All t-statistics are calculated using Newey and West (1987) adjusted standard errors using twelve lags.

Panel A: Value-weighted portfolios

	3 months				6 months				12 months			
Size group	Innovative	Non-innovative	Innovative premium	t-statistic (premium)	Innovative	Non-innovative	Innovative premium	t-statistic (premium)	Innovative	Non-innovative	Innovative premium	t-statistic (premium)
Small	1.31	0.97	0.34	(2.87)	1.32	0.99	0.32	(2.76)	1.35	1.03	0.32	(2.63)
Medium	1.20	1.03	0.17	(2.10)	1.21	1.05	0.16	(1.85)	1.21	1.05	0.16	(1.82)
Large	0.92	0.87	0.04	(0.57)	0.91	0.88	0.04	(0.50)	0.90	0.86	0.05	(0.61)
Small-Large	0.39	0.10	0.29	(2.74)	0.41	0.12	0.29	(2.73)	0.45	0.17	0.27	(2.53)

Panel B: Equal-weighted portfolios

	3 months				6 months				12 months			
Size group	Innovative	Non-innovative	Innovative premium	t-statistic (premium)	Innovative	Non-innovative	Innovative premium	t-statistic (premium)	Innovative	Non-innovative	Innovative premium	t-statistic (premium)
Small	1.45	1.02	0.43	(3.73)	1.47	1.05	0.42	(3.72)	1.5	1.10	0.41	(3.56)
Medium	1.24	1.05	0.18	(2.15)	1.25	1.06	0.19	(2.12)	1.25	1.04	0.21	(2.46)
Large	1.06	0.95	0.11	(1.43)	1.07	0.94	0.13	(1.71)	1.07	0.90	0.18	(2.19)
Small-Large	0.39	0.07	0.32	(3.45)	0.40	0.11	0.28	(3.09)	0.43	0.21	0.23	(2.42)

Table 2.3. Factor model-adjusted returns

This table presents future average monthly innovative premiums among small firms and factor loadings from regressions of innovative premiums on the Fama and French (2015) five-factor model. Small firms are firms in the three smallest NYSE size deciles. The innovative premium is the return from buying firms with at least one issued patent in the preceding twelve months and selling short all other firms. Raw returns are returns from the raw innovative premium. CAPM alphas are average monthly alphas from regressing the returns of the zero-investment portfolio on market returns in excess of the risk-free rate. FF3 alphas, Carhart alphas, FF3+liq. alphas, and FF5 alphas are average monthly alphas from regressing the returns of the zero-investment portfolio on the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, Fama and French (1993) three-factor model augmented by the traded Pástor and Stambaugh (2003) liquidity factor, and the Fama and French (2015) five-factor model. R_m-R_f is the coefficient on the CRSP value-weighted market return less the risk-free rate. SMB, HML, RMW, and CMA are coefficients on the size, book-to-market, profitability, and investment factor-mimicking portfolios. Panels A and C present results from value-weighted (VW) portfolios, and Panels B and D present results from equal-weighted (EW) portfolios. Portfolios are formed at the end of every month between June 1963 and November 2017 and held for either three, six, or twelve months. All *t*-statistics are in parentheses and calculated using Newey and West (1987) adjusted standard errors using twelve lags.

	Panel A: Innovative premium (VW)			Panel B: Innovative premium (EW)		
	3 months	6 months	12 months	3 months	6 months	12 months
Raw returns	0.34	0.32	0.32	0.43	0.42	0.41
	(2.87)	(2.76)	(2.63)	(3.73)	(3.72)	(3.56)
CAPM alphas	0.30	0.29	0.28	0.37	0.36	0.35
	(2.54)	(2.44)	(2.34)	(3.17)	(3.13)	(3.03)
FF3 alphas	0.33	0.33	0.33	0.40	0.39	0.38
	(2.64)	(2.53)	(2.46)	(3.28)	(3.25)	(3.17)
Carhart alphas	0.36	0.34	0.33	0.41	0.38	0.36
	(3.51)	(3.32)	(3.16)	(3.84)	(3.74)	(3.51)
FF3+liq. alphas	0.35	0.34	0.35	0.43	0.42	0.41
	(2.55)	(2.46)	(2.37)	(3.29)	(3.30)	(3.17)
FF5 alphas	0.42	0.42	0.44	0.46	0.44	0.44
	(3.64)	(3.46)	(3.40)	(4.04)	(3.89)	(3.71)

	Panel C: FF5 factor loadings (VW)			Panel D: FF5 factor loadings (EW)		
	3 months	6 months	12 months	3 months	6 months	12 months
R_m-R_f	0.00	0.00	-0.01	0.06	0.06	0.06
	(0.17)	(-0.09)	(-0.36)	(2.96)	(3.07)	(2.85)
SMB	0.10	0.12	0.12	0.10	0.11	0.11
	(2.11)	(2.13)	(2.17)	(2.55)	(2.61)	(2.48)
HML	-0.22	-0.24	-0.26	-0.20	-0.21	-0.23
	(-3.55)	(-3.40)	(-3.33)	(-3.56)	(-3.72)	(-3.78)
RMW	-0.34	-0.36	-0.39	-0.25	-0.24	-0.24
	(-3.62)	(-3.56)	(-3.87)	(-2.78)	(-2.59)	(-2.57)
CMA	0.17	0.17	0.16	0.14	0.16	0.18
	(1.54)	(1.57)	(1.47)	(1.43)	(1.57)	(1.67)

Table 2.4. Within-industry and industry-adjusted returns

This table presents future average monthly returns of small innovators and small non-innovators after adjusting for industry-level returns. Small firms are firms in the three smallest NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months and non-innovative otherwise. The innovative premium is the return from buying innovative firms and selling short non-innovative firms. Panel A presents average monthly returns over a twelve-month holding period within ten Fama-French industries (financials and utilities are excluded). Monthly portfolios in Panel A require at least five innovative and five non-innovative observations, otherwise that month is excluded. Observations is the number of monthly observations that fulfill this criteria. Panel B presents industry-adjusted innovative premiums in the first five columns and average FF5 alphas of the industry-adjusted innovative premium in the latter five columns. Industry-adjusted returns are calculated by subtracting the value-weighted industry return from each stock before forming portfolios. We use Fama-French 12, 30, and 48 (FF12, FF30, FF48) industry classifications and SIC two- and three-digit (SIC2, SIC3) codes. FF5 alphas are average monthly alphas from regressing the returns of the industry-adjusted zero-investment portfolio on the Fama and French (2015) five-factor model. Portfolios are value-weighted and formed at the end of every month between June 1963 and November 2017 and held for either three, six, or twelve months. All t-statistics are in parentheses and calculated using Newey and West (1987) adjusted standard errors using twelve lags.

Panel A: Within-industry monthly returns (12 months)

	Business equipment	Chemicals	Consumer durables	Consumer non-durables	Energy	Healthcare	Manufac-turing	Other	Shops	Telecoms
Innovative	1.47	1.46	1.29	1.20	0.62	1.43	1.30	1.20	1.14	0.00
Non-Innovative	0.99	1.17	0.88	0.97	0.42	1.17	1.08	0.88	1.24	0.35
Innovative premium	0.48	0.29	0.41	0.23	0.20	0.26	0.22	0.32	-0.10	-0.25
	(3.55)	(1.52)	(3.16)	(2.26)	(0.47)	(1.19)	(2.55)	(1.40)	(-0.44)	(-0.50)
Observations	643	643	643	643	151	557	643	613	485	144

Panel B: Innovative premium

	Industry-adjusted returns					Industry-adjusted FF5 alphas				
	FF12	FF30	FF48	SIC2	SIC3	FF12	FF30	FF48	SIC2	SIC3
3 Months	0.32	0.34	0.32	0.35	0.28	0.38	0.40	0.38	0.37	0.31
	(3.34)	(3.69)	(3.64)	(3.83)	(3.49)	(3.71)	(4.00)	(4.02)	(4.07)	(3.72)
6 Months	0.31	0.33	0.31	0.34	0.27	0.38	0.40	0.38	0.37	0.31
	(3.25)	(3.60)	(3.54)	(3.78)	(3.42)	(3.55)	(3.83)	(3.83)	(3.89)	(3.51)
12 Months	0.30	0.32	0.30	0.34	0.26	0.39	0.41	0.39	0.39	0.32
	(3.04)	(3.42)	(3.35)	(3.58)	(3.25)	(3.43)	(3.73)	(3.71)	(3.77)	(3.43)

Table 2.5. Subperiod analysis

This table presents future average monthly returns of small innovators and small non-innovators in different time periods. Small firms are firms in the three smallest NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months and non-innovative otherwise. The innovative premium is the return from buying innovative firms and selling short non-innovative firms. FF5 alphas are average monthly alphas from regressing the returns of the zero-investment portfolio on the Fama and French (2015) five-factor model. Panels A and B contain results from the 1963-1990 period, which begins July 1963 and ends December 1990. Panels C and D contain results from the 1991-2017 period, which begins January 1991 and ends December 2017. All portfolios are value-weighted and held for either three, six, or twelve months. All t-statistics are in parentheses and calculated using Newey and West (1987) adjusted standard errors using twelve lags.

	Panel A: Raw returns (1963-1990)			Panel B: FF5 alphas (1963-1990)		
	3 months	6 months	12 months	3 months	6 months	12 months
Innovative	1.22	1.23	1.27	-0.02	-0.03	0.03
	(3.08)	(3.10)	(3.16)	(-0.28)	(-0.31)	(0.33)
Non-innovative	1.03	1.05	1.09	-0.14	-0.14	-0.10
	(2.41)	(2.45)	(2.52)	(-2.80)	(-2.87)	(-2.05)
Innovative premium	0.19	0.18	0.18	0.12	0.11	0.13
	(1.92)	(1.79)	(1.75)	(1.10)	(1.05)	(1.23)

	Panel C: Raw returns (1991-2017)			Panel D: FF5 alphas (1991-2017)		
	3 months	6 months	12 months	3 months	6 months	12 months
Innovative	1.40	1.40	1.44	0.36	0.38	0.44
	(3.32)	(3.33)	(3.39)	(2.30)	(2.43)	(2.58)
Non-innovative	0.92	0.93	0.98	-0.23	-0.21	-0.17
	(2.61)	(2.67)	(2.85)	(-2.24)	(-2.24)	(-2.04)
Innovative premium	0.48	0.47	0.46	0.58	0.59	0.60
	(2.31)	(2.25)	(2.14)	(3.19)	(3.12)	(3.04)

Table 2.6. Fama-MacBeth regressions

This table presents time-series averages of results from monthly cross-sectional regressions (Fama and MacBeth, 1973) and includes only small firms. Monthly regressions of future one-month returns on innovative and controls are estimated between July 1963 through December 2017. Small firms are firms in the three smallest NYSE size deciles. Innovative equals one if the firm has been issued at least one patent in the preceding twelve months and zero otherwise. Book-to-market is book equity divided by market capitalization. Profitability is income before extraordinary items scaled by book equity. Asset growth is the percentage change in total assets over the last two fiscal years. Momentum is the cumulative raw return beginning twelve months ago through the month before last. Short-term reversal is the previous month's raw return. Illiquidity is the absolute stock return in the previous month divided by trading volume in the same month. Idiosyncratic volatility is the standard deviation of residuals from a regression of daily stock returns in excess of the risk-free rate on daily market returns in excess of the risk-free rate over the previous twelve months. Skewness is the total skewness of daily stock returns over the previous twelve months. Stock issuance is the annual percentage growth rate in split-adjusted shares. All non-dummy, independent variables are winsorized at the 1% and 99% levels each month and standardized to mean zero and unit standard deviation. Industry fixed effects are at the FF48 level. All t-statistics are in parentheses and calculated using Newey and West (1987) adjusted standard errors using twelve lags.

	(1)	(2)	(3)	(4)
Innovative	0.44***	0.37***	0.34***	0.23***
	(3.68)	(3.93)	(3.54)	(3.19)
ln(Book-to-market)		0.26***	0.29***	0.38***
		(4.10)	(4.57)	(7.01)
Profitability		0.39***	0.39***	0.42***
		(3.07)	(3.55)	(4.23)
Asset growth		-0.38***	-0.42***	-0.45***
		(-9.53)	(-8.41)	(-8.71)
Momentum		0.42***	0.44***	0.33***
		(3.76)	(3.93)	(3.19)
Short-term reversal			-1.02***	-1.14***
			(-8.79)	(-9.32)
Illiquidity			1.57***	1.45***
			(3.22)	(3.28)
Idiosyncratic volatility			-0.13	-0.18
			(-0.94)	(-1.32)
Skewness			-0.13***	-0.11***
			(-4.16)	(-3.37)
Stock issues			-0.20***	-0.19***
			(-3.13)	(-2.77)
Intercept	1.01***	1.02***	1.06***	1.02***
	(3.41)	(3.67)	(3.14)	(2.93)
Industry FEs	No	No	No	Yes
R^2	0.002	0.0258	0.0533	0.1070
Observations	1,542,408	1,110,646	1,041,656	1,041,656

Table 2.7. Long-run returns and volatilities

This table presents long-run future average monthly returns and volatilities of small innovators and small non-innovators in different holding periods. Small firms are firms in the three smallest NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months and non-innovative otherwise. The innovative premium is the return from buying innovative firms and selling short non-innovative firms. Panel A presents average monthly raw returns. Panel B presents average monthly FF5 alphas, which are average monthly alphas from regressing the returns of the zero-investment portfolio on the Fama and French (2015) five-factor model. Panel C presents standard deviations of monthly raw returns. Panel D presents standard deviations of monthly FF5 alphas. Each column presents results from the corresponding year over the five-year holding period. Portfolios are value-weighted and formed at the end of every month between June 1963 and November 2017 and for five years. All t-statistics in Panels A and B are in parentheses and calculated using Newey and West (1987) adjusted standard errors using twelve lags. The final rows in Panels C and D present p-values from F-tests for equality of standard deviations.

Panel A: Raw returns

	First year	Second year	Third year	Fourth year	Fifth year
Innovative	1.35	1.35	1.21	1.16	1.13
Non-innovative	1.03	1.10	1.04	1.04	0.97
Innovative premium	0.32	0.25	0.17	0.12	0.16
	(2.63)	(2.05)	(1.34)	(0.83)	(1.20)

Panel B: FF5 alphas

	First year	Second year	Third year	Fourth year	Fifth year
Innovative	0.30	0.40	0.34	0.32	0.38
	(3.01)	(3.55)	(3.05)	(2.67)	(3.11)
Non-innovative	-0.14	-0.03	-0.04	-0.02	0.00
	(-2.57)	(-0.53)	(-0.83)	(-0.31)	(-0.07)
Innovative premium	0.44	0.43	0.38	0.34	0.38
	(3.40)	(3.46)	(2.96)	(2.51)	(3.14)

Panel C: Volatilities of raw returns

	First year	Second year	Third year	Fourth year	Fifth year
Innovative	7.22%	7.28%	7.27%	7.24%	7.18%
Non-Innovative	6.46%	6.52%	6.52%	6.42%	6.46%
p-value	(0.005)	(0.006)	(0.007)	(0.003)	(0.010)

Panel D: Volatilities of FF5 alphas

	First year	Second year	Third year	Fourth year	Fifth year
Innovative	1.52%	1.61%	1.73%	1.81%	1.78%
Non-innovative	1.09%	1.02%	1.11%	1.12%	1.29%
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 2.8. Long-run volatilities of fundamentals

This table presents firm-level volatilities of fundamentals of small innovators and small non-innovators for five different percentiles. Small firms are firms in the three smallest NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months and non-innovative otherwise. Panel A presents future five-year cash flow (CF) volatilities. Cash flow is income before extraordinary expenses (net income) plus depreciation and amortization. Panel B presents future five-year net income (NI) volatilities. Panel C presents future five-year earnings per share (EPS) volatilities. Earnings per share is net income divided by shares outstanding. Panel D presents future five-year return on assets (ROA) volatilities. Return on assets is net income divided by total assets. Panel E presents future five-year return on book equity (ROE) volatilities. Return on book equity is net income divided by book equity. Due to the necessity of five years of future data, these panels include observations from 1963 through 2012.

Panel A: Five-year CF volatilities

	P10	P25	P50	P75	P90
Innovative	0.59	1.41	3.99	11.0	26.3
Non-innovative	0.41	0.93	2.62	7.65	20.3

Panel B: Five-year NI volatilities

	P10	P25	P50	P75	P90
Innovative	0.55	1.33	3.85	10.6	26.1
Non-innovative	0.38	0.86	2.43	7.24	19.5

Panel C: Five-year EPS volatilities

	P10	P25	P50	P75	P90
Innovative	0.14	0.25	0.48	0.87	1.49
Non-innovative	0.12	0.22	0.42	0.81	1.49

Panel D: Five-year ROA volatilities

	P10	P25	P50	P75	P90
Innovative	1.14%	2.02%	4.33%	10.7%	23.2%
Non-innovative	1.02%	1.84%	3.81%	8.80%	19.2%

Panel E: Five-year ROE volatilities

	P10	P25	P50	P75	P90
Innovative	1.89%	3.34%	7.15%	18.0%	44.6%
Non-innovative	1.80%	3.24%	6.88%	16.9%	43.5%

Table 2.9. Investor attention and returns

This table presents future average monthly returns of small innovators after sorting by investor attention (i.e., IBES earnings estimates). Small firms are firms in the three smallest NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months. We label firms with no IBES earnings estimates in the previous twelve months as no IBES. We sort firms with at least one IBES earnings estimate in the previous twelve months into IBES estimate groups based on breakpoints for the bottom 30% (lowest), middle 40% (mid), and top 30% (highest). Panel A presents average monthly raw returns. Panel B provides average monthly FF5 alphas, which are average monthly alphas from regressing the returns of the zero-investment portfolio on the Fama and French (2015) five-factor model. Portfolios are value-weighted and formed at the end of every month between December 1983 and November 2017 and held for either three, six, or twelve months. All t-statistics are in parentheses and calculated using Newey and West (1987) adjusted standard errors using twelve lags.

Panel A: Raw returns

	3 months	6 months	12 months
No IBES	1.04	1.05	1.11
Lowest	1.36	1.37	1.42
Mid	1.36	1.44	1.45
Highest	1.53	1.56	1.67
No IBES-highest	-0.49	-0.51	-0.57
	(-2.82)	(-3.15)	(-3.95)

Panel B: FF5 alphas

	3 months	6 months	12 months
No IBES	0.17	0.18	0.24
	(1.30)	(1.30)	(1.55)
Lowest	0.48	0.44	0.52
	(3.03)	(3.49)	(3.09)
Mid	0.40	0.53	0.54
	(2.60)	(3.10)	(3.15)
Highest	0.43	0.43	0.57
	(2.02)	(2.46)	(3.80)
No IBES-highest	-0.26	-0.24	-0.33
	(-1.09)	(-1.14)	(-1.83)

Table 2.10. Innovative persistence and returns

This table presents future average monthly returns of small innovators after sorting by innovative persistence. Small firms are firms in the three smallest NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months. We define firms as sporadic innovators if they did not receive any patents in the four years before the preceding twelve months. We sort firms with at least one patent in the four years before the preceding twelve months into three innovative persistence groups based on breakpoints for the bottom 30% (least), middle 40% (mid), and top 30% (most). We define innovative persistence by the number of months during those four years firms were issued at least one patent. Panel A presents average monthly raw returns. Panel B provides average monthly FF5 alphas, which are average monthly alphas from regressing the returns of the zero-investment portfolio on the Fama and French (2015) five-factor model. Portfolios are value-weighted and formed at the end of every month between June 1967 and November 2017 and held for either three, six, or twelve months. All t-statistics are in parentheses and calculated using Newey and West (1987) adjusted standard errors using twelve lags.

Panel A: Raw returns

	3 months	6 months	12 months
Sporadic	0.97	1.01	1.03
Least	1.19	1.20	1.19
Mid	1.25	1.25	1.26
Most	1.44	1.43	1.41
Most-sporadic	0.47	0.42	0.39
	(3.19)	(3.11)	(3.17)

Panel B: FF5 alphas

	3 months	6 months	12 months
Sporadic	0.00	0.07	0.16
	(-0.02)	(0.61)	(1.45)
Least	0.17	0.18	0.24
	(1.44)	(1.58)	(2.05)
Mid	0.25	0.27	0.35
	(2.44)	(2.49)	(2.88)
Most	0.43	0.42	0.46
	(2.92)	(2.93)	(3.08)
Most-sporadic	0.43	0.35	0.30
	(2.37)	(2.06)	(1.93)

Table 2.11. Relative patent assets and returns

This table presents future average monthly returns of small innovators and large innovators after sorting by relative patent assets. Small firms are firms in the three smallest NYSE size deciles. Large firms are firms in the three largest NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months. We sort firms into three relative patent assets groups based on breakpoints for the bottom 30% (least), middle 40% (mid), and top 30% (most). We define relative patent assets as patent assets divided by market capitalization. Total patent assets are estimated using the perpetual inventory method (methodology detailed in Section 2.5.1). Panel A presents average monthly raw returns. Panel B presents average monthly FF5 alphas, which are average monthly alphas from regressing the returns of the zero-investment portfolio on the Fama and French (2015) five-factor model. Portfolios are value-weighted and formed at the end of every month between June 1963 and November 2017 and held for either three, six, or twelve months. All t-statistics are in parentheses and calculated using Newey and West (1987) adjusted standard errors using twelve lags.

Panel A: Raw returns

	Small innovators			Large innovators		
	3 months	6 months	12 months	3 months	6 months	12 months
Lowest	1.24	1.26	1.27	0.88	0.88	0.85
Mid	1.22	1.22	1.27	0.91	0.91	0.89
Highest	1.49	1.50	1.54	0.96	0.96	0.96
Highest-lowest	0.25	0.25	0.27	0.08	0.08	0.11
	(2.11)	(2.06)	(2.27)	(0.85)	(0.78)	(1.17)

Panel B: FF5 alphas

	Small innovators			Large innovators		
	3 months	6 months	12 months	3 months	6 months	12 months
Lowest	0.20	0.22	0.27	0.15	0.15	0.12
	(2.54)	(2.61)	(2.87)	(2.07)	(2.03)	(1.75)
Mid	0.14	0.15	0.22	0.14	0.15	0.15
	(1.55)	(1.64)	(2.14)	(2.33)	(2.68)	(2.73)
Highest	0.41	0.41	0.46	0.09	0.07	0.07
	(2.97)	(3.07)	(3.29)	(1.80)	(1.46)	(1.59)
Highest-lowest	0.21	0.19	0.20	-0.06	-0.08	-0.05
	(1.64)	(1.60)	(1.84)	(-0.59)	(-0.81)	(-0.53)

Table 2.12. Product innovation and returns

This table presents future average monthly returns of small innovators and large innovators after sorting by the number of product innovation claims in the previous twelve months. Small firms are firms in the three smallest NYSE size deciles. Large firms are firms in the three largest NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months. We sort firms into three product innovation claims groups based on breakpoints for the bottom 30% (fewest), middle 40% (mid), and top 30% (most). Panel A presents average monthly raw returns. Panel B presents average monthly FF5 alphas, which are average monthly alphas from regressing the returns of the zero-investment portfolio on the Fama and French (2015) five-factor model. Portfolios are value-weighted and formed at the end of every month between December 1976 and December 2012 and held for either three, six, or twelve months. All t-statistics are in parentheses and calculated using Newey and West (1987) adjusted standard errors using twelve lags.

Panel A: Raw returns

	Small innovators			Large innovators		
	3 months	6 months	12 months	3 months	6 months	12 months
Fewest	1.19	1.19	1.22	0.94	0.97	0.99
Mid	1.27	1.28	1.30	1.09	1.09	1.11
Most	1.48	1.50	1.53	0.98	0.99	1.00
Most-fewest	0.30	0.30	0.31	0.03	0.02	0.02
	(3.14)	(3.20)	(3.44)	(0.34)	(0.19)	(0.16)

Panel B: FF5 alphas

	Small innovators			Large innovators		
	3 months	6 months	12 months	3 months	6 months	12 months
Fewest	0.14	0.14	0.22	0.12	0.14	0.12
	(1.23)	(1.25)	(1.62)	(1.53)	(1.68)	(1.53)
Mid	0.18	0.20	0.24	0.09	0.08	0.08
	(1.46)	(1.69)	(2.10)	(1.34)	(1.20)	(1.26)
Most	0.31	0.34	0.41	0.14	0.14	0.14
	(2.12)	(2.28)	(2.45)	(2.19)	(2.20)	(2.12)
Most-fewest	0.17	0.19	0.19	0.02	0.00	0.01
	(1.74)	(1.99)	(2.09)	(0.20)	(0.02)	(0.12)

Table 2.13. Organization capital and returns

This table presents future average monthly returns of small innovators, small non-innovators, large innovators, and large non-innovators after sorting by organization capital. Small firms are firms in the three smallest NYSE size deciles. Large firms are firms in the three largest NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months and non-innovative otherwise. Within each FF48 industry, we sort firms into three groups based on organization capital (i.e., organization capital divided by total assets) breakpoints for the bottom 30% (lowest), middle 40% (mid), and top 30% (highest). Panel A presents average monthly raw returns. Panel B provides average monthly FF5 alphas, which are average monthly alphas from regressing the returns of the zero-investment portfolio on the Fama and French (2015) five-factor model. Portfolios are value-weighted and formed at the end of every month between June 1963 and November 2017 and held for either three, six, or twelve months. All t-statistics are in parentheses and calculated using Newey and West (1987) adjusted standard errors using twelve lags.

Panel A: Raw returns

	Small innovators			Small non-innovators			Large innovators			Large non-innovators		
	3 months	6 months	12 months	3 months	6 months	12 months	3 months	6 months	12 months	3 months	6 months	12 months
Lowest	1.03	1.06	1.16	0.84	0.87	0.94	0.90	0.90	0.89	0.77	0.80	0.79
Mid	1.39	1.37	1.40	1.06	1.08	1.10	0.92	0.92	0.91	0.94	0.93	0.90
Highest	1.53	1.52	1.50	1.17	1.18	1.20	0.93	0.94	0.94	0.90	0.91	0.90
Highest-lowest	0.51	0.45	0.34	0.33	0.32	0.27	0.03	0.04	0.05	0.13	0.12	0.11
	(4.48)	(3.57)	(2.56)	(4.94)	(5.16)	(4.64)	(0.37)	(0.45)	(0.64)	(1.27)	(1.25)	(1.15)

Panel B: FF5 alphas

	Small innovators			Small non-innovators			Large innovators			Large non-innovators		
	3 months	6 months	12 months	3 months	6 months	12 months	3 months	6 months	12 months	3 months	6 months	12 months
Lowest	0.02	0.07	0.19	-0.33	-0.32	-0.25	0.11	0.11	0.10	-0.19	-0.17	-0.19
	(0.18)	(0.60)	(1.37)	(-3.46)	(-3.72)	(-3.56)	(1.68)	(1.75)	(1.61)	(-1.65)	(-1.50)	(-1.65)
Mid	0.29	0.26	0.30	-0.14	-0.13	-0.11	0.16	0.16	0.14	0.02	0.00	-0.03
	(3.03)	(2.67)	(2.89)	(-1.87)	(-2.00)	(-1.92)	(3.38)	(3.25)	(3.11)	(0.31)	(-0.01)	(-0.49)
Highest	0.40	0.39	0.40	-0.03	-0.01	0.01	0.07	0.07	0.08	-0.10	-0.08	-0.10
	(4.33)	(4.28)	(4.20)	(-0.38)	(-0.17)	(0.25)	(1.50)	(1.62)	(1.85)	(-1.26)	(-1.06)	(-1.31)
Highest-lowest	0.38	0.31	0.21	0.30	0.32	0.27	-0.04	-0.04	-0.02	0.09	0.09	0.08
	(3.77)	(2.71)	(1.69)	(3.70)	(4.03)	(4.15)	(-0.49)	(-0.47)	(-0.21)	(0.96)	(1.01)	(0.91)

APPENDIX A. SUPPLEMENTARY CHAPTER 1 TABLES

Table A.1. Investment and q: Ordinary least squares

This table presents results from ordinary least squares regressions of investment on lagged q, firm fixed effects, and year fixed effects. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). Intangible investment is scaled R&D expenses (set to zero if missing) plus 30% of scaled SG&A expenses. Total investment (PT) is scaled capital expenditures plus intangible investment. All investment variables are scaled by the denominator of lagged q being regressed on by investment. Within R^2 estimates are ordinary R^2 estimates from estimating OLS on the transformed data. ΔR^2 is the R^2 estimate associated with PI q minus the R^2 estimate associated with either physical q (columns 2 and 5) or total q (columns 3 and 6) within each investment type. Standard errors in parentheses are clustered by firm. Panel A presents results for all firms. Panel B presents results for firms with patent capital at any point during the sample period. Standard errors below R^2 estimates and ΔR^2 estimates are estimated using influence functions. Bolded estimates are significant at the 5% level.

Panel A: All firms

	Intangible investment			Total investment (PT)		
	(1)	(2)	(3)	(4)	(5)	(6)
PI q	**0.039**			**0.067**		
	(0.0006)			(0.0008)		
Physical q		**0.030**			**0.047**	
		(0.0006)			(0.0007)	
Total q			**0.020**			**0.051**
			(0.0003)			(0.0007)
Within R^2	0.308	0.275	0.205	0.343	0.297	0.243
	(0.055)	(0.057)	(0.004)	(0.005)	(0.005)	(0.004)
ΔR^2	-	**0.033**	**0.103**	-	**0.046**	**0.100**
	-	(0.005)	(0.004)	-	(0.004)	(0.004)
Obs.	155,470	155,470	155,470	155,470	155,470	155,470

Panel B: Firms with patent capital

	Intangible investment			Total investment (PT)		
	(1)	(2)	(3)	(4)	(5)	(6)
PI q	**0.049**			**0.070**		
	(0.0009)			(0.0011)		
Physical q		**0.032**			**0.044**	
		(0.0008)			(0.0009)	
Total q			**0.024**			**0.044**
			(0.0005)			(0.0008)
Within R^2	0.384	0.314	0.253	0.418	0.339	0.293
	(0.008)	(0.008)	(0.006)	(0.007)	(0.008)	(0.005)
ΔR^2	-	**0.070**	**0.131**	-	**0.079**	**0.125**
	-	(0.007)	(0.006)	-	(0.007)	(0.006)
Obs.	76,297	76,297	76,297	76,297	76,297	76,297

Table A.2. Investment and q: Cumulant estimator

This table presents results from cumulant estimator regressions of investment on lagged q, firm fixed effects, and year fixed effects. The numerator of each proxy for q is the market value of common equity plus the book value of short- and long-term debt minus the book value of current assets. The denominator of each proxy for q contains physical capital (book value of gross property, plant, and equipment). The denominator of PI q also includes my estimate of intangible capital (i.e., patent capital plus on-balance sheet intangible capital). The denominator of total q also includes intangible capital as estimated by Peters and Taylor (2017). Intangible investment is scaled R&D expenses (set to zero if missing) plus 30% of scaled SG&A expenses. Total investment (PT) is scaled capital expenditures plus intangible investment. All investment variables are scaled by the denominator of lagged q being regressed on by investment. ρ^2 is the within R^2 estimate from the hypothetical regression of investment on marginal q. τ^2 is the within R^2 estimate from the hypothetical regression of estimated q on marginal q. Panel A presents results for all firms. Panel B presents results for firms with patent capital at any point during the sample period. Standard errors in parentheses are estimated using influence functions and are clustered by firm. Bolded coefficients are significant at the 5% level.

Panel A: All firms

	Intangible investment			Total investment (PT)		
	(1)	(2)	(3)	(4)	(5)	(6)
PI q	**0.066**			**0.101**		
	(0.0009)			(0.0010)		
Physical q		**0.054**			**0.078**	
		(0.0010)			(0.0011)	
Total q			**0.037**			**0.088**
			(0.0006)			(0.0011)
ρ^2	0.512	0.497	0.390	0.515	0.491	0.417
	(0.011)	(0.014)	(0.010)	(0.010)	(0.012)	(0.009)
τ^2	0.602	0.553	0.525	0.665	0.604	0.583
	(0.015)	(0.016)	(0.013)	(0.013)	(0.014)	(0.012)
Obs.	155,470	155,470	155,470	155,470	155,470	155,470

Panel B: Firms with patent capital

	Intangible investment			Total investment (PT)		
	(1)	(2)	(3)	(4)	(5)	(6)
PI q	**0.073**			**0.099**		
	(0.0012)			(0.0013)		
Physical q		**0.054**			**0.069**	
		(0.0014)			(0.0015)	
Total q			**0.039**			**0.067**
			(0.0008)			(0.0010)
ρ^2	0.574	0.523	0.423	0.587	0.531	0.449
	(0.015)	(0.019)	(0.013)	(0.014)	(0.018)	(0.013)
τ^2	0.669	0.600	0.600	0.712	0.638	0.652
	(0.019)	(0.023)	(0.020)	(0.017)	(0.021)	(0.018)
Obs.	76,297	76,297	76,297	76,297	76,297	76,297

APPENDIX B. SUPPLEMENTARY CHAPTER 2 TABLES

Table B.1. Returns to innovation by size decile

This table presents future average monthly returns of innovative firms and non-innovative firms after sorting firms into NYSE size deciles. We define firms as innovative if they have been issued at least one patent in the preceding twelve months and non-innovative otherwise. The innovative premium is the return from buying innovative firms and selling short non-innovative firms. Panel A presents results from value-weighted portfolios, and Panel B presents results from equal-weighted portfolios. Portfolios are formed at the end of every month between June 1963 and November 2017 and held for either three, six, or twelve months. All t-statistics are calculated using Newey and West (1987) adjusted standard errors using twelve lags.

Panel A: Value-weighted portfolios

	3 months				6 months				12 months			
Size decile	Innovative	Non-innovative	Innovative premium	t-statistic (premium)	Innovative	Non-innovative	Innovative premium	t-statistic (premium)	Innovative	Non-innovative	Innovative premium	t-statistic (premium)
1	1.38	0.92	0.47	(3.85)	1.44	0.97	0.47	(3.88)	1.49	1.03	0.45	(3.40)
2	1.28	0.97	0.31	(2.40)	1.28	1.00	0.28	(2.05)	1.33	1.02	0.31	(2.20)
3	1.30	1.05	0.25	(2.06)	1.29	1.02	0.26	(2.32)	1.31	1.05	0.26	(2.32)
4	1.16	1.04	0.11	(1.17)	1.19	1.07	0.12	(1.19)	1.21	1.09	0.13	(1.24)
5	1.26	1.09	0.18	(1.66)	1.26	1.09	0.17	(1.58)	1.26	1.09	0.17	(1.60)
6	1.24	1.00	0.24	(2.61)	1.21	1.02	0.20	(2.14)	1.22	1.04	0.18	(2.02)
7	1.18	1.02	0.15	(1.71)	1.19	1.04	0.16	(1.70)	1.19	1.03	0.17	(1.82)
8	1.12	1.05	0.07	(0.78)	1.13	1.04	0.10	(1.06)	1.14	1.01	0.14	(1.41)
9	1.11	0.88	0.23	(2.64)	1.11	0.89	0.22	(2.41)	1.11	0.88	0.23	(2.49)
10	0.88	0.80	0.08	(0.96)	0.88	0.81	0.07	(0.88)	0.87	0.79	0.08	(1.01)
1-10	0.50	0.11	0.39	(3.42)	0.56	0.16	0.40	(3.60)	0.63	0.24	0.38	(3.08)

Panel B: Equal-weighted portfolios

	3 months				6 months				12 months			
Size decile	Innovative	Non-innovative	Innovative premium	t-statistic (premium)	Innovative	Non-innovative	Innovative premium	t-statistic (premium)	Innovative	Non-innovative	Innovative premium	t-statistic (premium)
1	1.56	1.03	0.53	(4.61)	1.60	1.08	0.52	(4.64)	1.64	1.15	0.49	(4.18)
2	1.32	0.98	0.34	(2.59)	1.31	1.00	0.32	(2.38)	1.35	0.97	0.38	(2.83)
3	1.34	1.06	0.28	(2.28)	1.34	1.01	0.33	(2.83)	1.35	1.00	0.34	(3.09)
4	1.19	1.06	0.14	(1.39)	1.23	1.07	0.16	(1.57)	1.24	1.05	0.19	(1.99)
5	1.29	1.10	0.19	(1.73)	1.29	1.09	0.20	(1.90)	1.29	1.05	0.24	(2.32)
6	1.27	1.02	0.25	(2.78)	1.25	1.03	0.22	(2.44)	1.25	1.03	0.23	(2.62)
7	1.20	1.02	0.18	(1.93)	1.22	1.02	0.19	(2.05)	1.21	1.00	0.20	(2.36)
8	1.14	1.05	0.09	(0.99)	1.17	1.03	0.13	(1.45)	1.16	0.98	0.19	(2.00)
9	1.13	0.90	0.23	(2.59)	1.14	0.89	0.25	(2.55)	1.14	0.87	0.28	(2.81)
10	0.94	0.82	0.12	(1.49)	0.95	0.81	0.14	(1.71)	0.94	0.76	0.18	(2.31)
1-10	0.62	0.21	0.41	(3.86)	0.65	0.27	0.39	(3.75)	0.70	0.39	0.31	(2.87)

Table B.2. Returns to innovation by size: Alternative innovative criteria

This table presents future average monthly innovative premiums when using alternative criteria to identify innovative firms. Small firms are firms in the three smallest NYSE size deciles, and large firms are firms in the largest three NYSE size deciles. The main results are in the first row of each panel, in which we define firms as innovative if they have been issued at least one patent in the preceding twelve months. In the second, third, fourth, and fifth rows of each panel, we define firms as innovative if they have been issued at least one patent in the previous six months, one patent in the previous eighteen months, two patents in the previous twelve months, or five patents in the previous twelve months. In the sixth and seventh rows of Panels C and D, we define large firms as innovative if they have been issued at least 25 patents in the previous twelve months or 50 patents in the previous twelve months. For each row, if we do not define firms as innovative, we define them as non-innovative. The innovative premium is the return from buying innovative firms and selling short non-innovative firms. Panels A and C present results from value-weighted (VW) portfolios, and Panels B and D present results from equal-weighted (EW) portfolios. Portfolios are formed at the end of every month between June 1963 and November 2017 and held for either three, six, or twelve months. All t-statistics are in parentheses and calculated using Newey and West (1987) adjusted standard errors using twelve lags.

	Panel A: Small innovators (VW)			Panel B: Small innovators (EW)		
	3 months	6 months	12 months	3 months	6 months	12 months
≥1 patent past 12 months	0.34	0.32	0.32	0.43	0.42	0.41
	(2.87)	(2.76)	(2.63)	(3.73)	(3.72)	(3.56)
≥1 patent past 6 months	0.34	0.33	0.33	0.45	0.44	0.43
	(2.89)	(2.89)	(2.73)	(3.78)	(3.84)	(3.70)
≥1 patent past 18 months	0.35	0.33	0.32	0.43	0.42	0.40
	(2.98)	(2.81)	(2.61)	(3.85)	(3.78)	(3.56)
≥2 patents past 12 months	0.38	0.37	0.36	0.48	0.48	0.46
	(3.09)	(3.05)	(2.88)	(3.81)	(3.83)	(3.66)
≥5 patents past 12 months	0.46	0.46	0.48	0.56	0.55	0.57
	(3.55)	(3.57)	(3.64)	(4.03)	(3.94)	(4.03)

	Panel C: Large innovators (VW)			Panel D: Large innovators (EW)		
	3 months	6 months	12 months	3 months	6 months	12 months
≥1 patent past 12 months	0.04	0.04	0.05	0.11	0.13	0.18
	(0.57)	(0.50)	(0.61)	(1.43)	(1.71)	(2.19)
≥1 patent past 6 months	0.06	0.05	0.05	0.13	0.14	0.17
	(0.79)	(0.66)	(0.71)	(1.78)	(1.90)	(2.19)
≥1 patent past 18 months	0.05	0.04	0.05	0.13	0.15	0.18
	(0.67)	(0.54)	(0.59)	(1.68)	(1.88)	(2.28)
≥2 patents past 12 months	0.06	0.05	0.06	0.12	0.15	0.18
	(0.76)	(0.71)	(0.81)	(1.58)	(1.88)	(2.26)
≥5 patents past 12 months	0.07	0.06	0.06	0.13	0.15	0.16
	(0.99)	(0.87)	(0.92)	(1.76)	(1.98)	(2.16)
≥25 patents past 12 months	0.10	0.09	0.09	0.18	0.18	0.20
	(1.55)	(1.35)	(1.35)	(2.79)	(2.81)	(2.97)
≥50 patents past 12 months	0.05	0.05	0.05	0.19	0.19	0.21
	(0.81)	(0.71)	(0.82)	(2.87)	(2.92)	(3.14)

APPENDIX C. SUPPLEMENTARY CHAPTER 2 METHODOLOGY

Estimated patent values

This section describes how we estimate patent values and how our methodology differs from that in Kogan et al. (2017). For complete details of the estimation procedure, please see Section II.D. of Kogan et al. (2017).

The idiosyncratic stock return R (i.e., firm's return minus the return on the CRSP value-weighted portfolio) for a given firm around the time that its patent j is issued is

$$R_j = v_j + \varepsilon_j, \tag{C.1}$$

in which v_j denotes the value of patent j, as a fraction of the firm's market capitalization, and ε_j denotes the component of the firm's stock return that is unrelated to the patent.

The estimated economic value ξ of patent j is estimated as

$$\xi_j = M_j(1-\bar{\pi})^{-1}\frac{1}{N_j}E[v_j|R_j], \tag{C.2}$$

in which M_j is the market capitalization of the firm that is issued patent j on the day prior to the announcement of the patent issuance, and $\bar{\pi}$ is the unconditional probability of a successful patent application, which is approximately 56% of all progenitor applications (i.e., applications unrelated to any previously filed U.S. patent application) filed between 1996 and 2005 and examined before mid-2013 (Carley et al., 2015). If multiple patents N_j are issued to the same firm on the same day as patent j, each patent is assigned fraction $1/N_j$ of the total value.

Since the market value of the patent v is assumed to be a positive random variable, v is distributed according to a normal distribution truncated at 0, $v_j \sim \mathcal{N}^+(0, \sigma^2_{vft})$. The noise term is assumed to be normally distributed, $\varepsilon_j \sim \mathcal{N}(0, \sigma^2_{\varepsilon ft})$. The filtered value of v_j, as a function of the idiosyncratic stock return R, is equal to

$$E[v_j|R_j] = \delta_{ft} R_j + \sqrt{\delta_{ft}}\sigma_{\varepsilon ft} \frac{\phi\Big(-\sqrt{\delta_{ft}}\frac{R_j}{\sigma_{\varepsilon ft}}\Big)}{1 - \Phi\Big(-\sqrt{\delta_{ft}}\frac{R_j}{\sigma_{\varepsilon ft}}\Big)}, \tag{C.3}$$

in which ϕ and Φ are the standard normal pdf and cdf, and δ is the signal-to-noise ratio,

$$\delta_{ft} = \frac{\sigma^2_{vft}}{\sigma^2_{vft} + \sigma^2_{\varepsilon ft}}. \tag{C.4}$$

Up until this point, the estimation procedure used in this paper is the same as that in Kogan et al. (2017). The parameters σ^2_{vft} and $\sigma^2_{\varepsilon ft}$ need to be estimated. To do so, Kogan et al. (2017), specify that the signal-to-noise ratio is constant across firms and time (i.e., $\delta_{ft} = \delta$). To avoid using future information, we allow the signal-to-noise ratio to vary over time but remain constant across firms (i.e., $\delta_{ft} = \delta_t$). To estimate δ_t, we use γ_t to estimate the increase in the volatility of firm returns around patent announcement days from

$$log(R_{fd})^2 = \gamma_t I_{fd} + c_t Z_{fd} + u_{fdt}, \tag{C.5}$$

in which R_{fd} is the three-day idiosyncratic return of firm f beginning on day d, and I_{fd} is a patent issue-day dummy. In each estimation, the sample is restricted to firms that have been granted at least one patent through month t, so every month, γ_t is updated to reflect all available information through that month. Controls Z_{fd} include day of the week and firm interacted with calendar month fixed effects (Kogan et al., 2017 use year fixed effects). The signal-to-noise estimate is recovered from the one-month lagged estimated value of γ_t,

$$\widehat{\delta_t} = 1 - e^{-\widehat{\gamma_{t-1}}}. \tag{C.6}$$

The last step in estimating equation (3) involves estimating the variance of the measurement error $\sigma^2_{\varepsilon ft}$. This estimate is accomplished nonparametrically by using the sum of squared market-adjusted returns, and while Kogan et al. (2017) allow this estimate to vary at an annual frequency (Andersen and Teräsvirta, 2009), we do so at a monthly frequency. Specifically, we use a rolling twelve-month period to provide a monthly update to the estimate of $\sigma^2_{\varepsilon ft}$. To obtain $\sigma^2_{\varepsilon ft}$, the realized mean idiosyncratic squared returns, σ^2_{ft}, is estimated using the squared residual from a rolling twelve-month regression of daily firm returns on daily CRSP value-weighted returns (i.e., estimated idiosyncratic volatility is updated on a monthly basis). Since σ^2_{ft} is estimated over both announcement and non-announcement days, it is comprised of both σ^2_{vft} and $\sigma^2_{\varepsilon ft}$. Given the estimate of σ^2_{ft}, the fraction of trading days that are announcement days, d_{ft}, and $\widehat{\gamma}_t$, the variance of the measurement error can be estimated, but once again, to ensure that we are not using any future information, we use one-month lagged parameters: $\sigma^2_{\varepsilon ft} = 3\sigma^2_{ft-1}\big(1 + 3d_{ft-1}(e^{\widehat{\gamma_{t-1}}} - 1)\big)^{-1}$.

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