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Product market competition, R&D investment, and stock returns☆

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ABSTRACT

A standard real options model predicts a strong positive interaction effect between research and development (R&D) investment and product market competition. R&D-intensive firms tend to be riskier and earn higher expected returns than R&D-weak firms, particularly in competitive industries. Also, firms in competitive industries earn higher expected returns than firms in concentrated industries, especially among R&D-intensive firms. Intuitively, R&D projects are more likely to fail in the presence of more competition because rival firms could win the innovation race. Empirical evidence largely supports the model's predictions.

1. Introduction

Investment in research and development (R&D) is one of the most important activities driving companies' long-term viability. A substantial portion of firms listed on the US stock market invest aggressively in R&D, and firms in competitive industries frequently enter into innovation races with many rivals. When one firm successfully completes an R&D project before other firms in an innovation race, these other firms often suspend or even abandon similar projects. Suspending or abandoning an R&D project significantly reduces firm value, for doing so prevents projected cash flows associated with the R&D project from being realized, and R&D investment tends to be irreversible. Therefore, competition can have a substantial impact on R&D-intensive firms.

This paper studies the joint effect of product market competition and R&D investment on stock returns. Based on a real options model developed by Berk, Green, and Naik (2004) for a multistage R&D venture, I establish two new testable hypotheses: (1) the positive R&D-return relation is stronger in competitive industries, and (2) the positive competition-return relation is stronger among R&D-intensive firms. In other words, competition and R&D

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investment have a strong positive interaction effect on expected stock returns.

In the model, the firm progresses through the R&D project in sequential stages and decides whether or not to incur an instantaneous R&D investment to continue the project. Prior to completing the project, the decision maker can observe future cash flows that the project would be producing if it were completed today. Because the risk associated with cash flows has a systematic component, this feature imparts a substantial amount of systematic risk to the project, making the R&D venture a series of compound options on systematic uncertainty. Because options have higher systematic risk than the underlying asset due to the implicit leverage in options, the R&D venture demands a higher risk premium than the stochastic cash flow itself.

Competition increases the probability that potential future cash flows will be extinguished and in turn decreases the benefits of R&D investing and raises the chances that the project will be suspended if adverse shocks to future cash flows occur. Therefore, firms' investment decisions and value are more sensitive to the systematic risk associated with these cash flows. Although the risk of competition is idiosyncratic, it raises the exercise threshold for successive R&D investment options, thereby levering the firm's exposure to systematic risk. As an intuitive comparison, in the Black and Scholes model, the elasticity of a call option with respect to the underlying risk is increased as the distance to exercise increases. Moreover, firms with high R&D inputs face even greater negative impacts from extinguished potential cash flows, for these inputs further reduce the value of investment options. Thus, the model predicts a stronger positive relation between competition and expected returns among R&D-intensive firms. Analogously, the model also predicts a stronger positive relation between R&D investment and expected returns for firms in highly competitive industries.

Using a conventional double-sorting approach, I test the model's predictions empirically and show a robust positive interaction effect between product market competition and R&D investment on stock returns. The tests reveal that the positive R&D-return relation exists only in competitive industries. The raw returns and the abnormal returns (i.e., alpha in the asset pricing model) on the double-sorted portfolios increase monotonically with R&D intensity for firms in competitive industries. However, this return pattern does not exist for firms in concentrated industries. This finding holds for all three asset pricing models—the Carhart (1997) four-factor model, the Hou, Xue, and Zhang (2015) q-factor model, and the Fama and French (2015) five-factor model—as well as for both NYSE breakpoints and all-but-micro breakpoints. For instance, when analyzed using all-but-micro breakpoints, the monthly equal-weighted q-factor alphas on the low, medium, and high R&D-intensity portfolios in competitive industries are 0.10%, 0.48%, and 0.77%, respectively, with t-statistics of 0.92, 5.17, and 5.70. Further, the q-factor alpha on the high-minus-low R&D-intensity portfolio is as high as 67 basis points per month and statistically significant at the 1% level. In contrast, the monthly equal-weighted q-factor alphas on the low, medium, and high R&D-intensity portfolios in concentrated industries are much smaller and insignificant: -0.06%, -0.18%, and 0.07%, respectively, with t-statistics of 0.38, 1.24, and 0.34. This translates to a monthly alpha spread of only 0.13% with a t-statistic of 0.56. Moreover, when analyzed using NYSE breakpoints, the value-weighted q-factor alpha on the high-minus-low R&D-intensity portfolio is 50 basis points per month in competitive industries, whereas it is -0.29% in concentrated industries.

I also find that the positive competition-return relation exists only among R&D-intensive firms. The portfolio raw return and abnormal return increase monotonically with the degree of competition among firms with high R&D inputs, but this pattern does not exist among firms with low R&D inputs. This finding is robust for all three asset pricing models, as well as for both NYSE breakpoints and all-but-micro breakpoints. For example, when analyzed using all-but-micro breakpoints, the monthly equal-weighted q-factor alphas on the low, medium, and high competition portfolios among R&D-intensive firms are 0.07%, 0.02%, and 0.77%, respectively, with t-statistics of 0.34, 0.11, and 5.70. Further, the q-factor alpha on the high-minus-low competition portfolio is 0.70% and statistically significant at the 1% level. In contrast, for firms with low R&D inputs, the alphas on the competition portfolios are always small and insignificant. The monthly q-factor alpha on the high-minus-low competition portfolio is -0.14% with a t-statistic of 1.09.

These return patterns also hold under numerous robustness tests, from measuring competition with an alternative industry concentration measure to using different sorting methods or including more factors in the asset pricing model. More important, by performing subsample studies, I verify that my findings are not driven by financial constraints and innovation ability that have been identified by Li (2011) and Cohen, Diether, and Malloy (2013) as factors that affect R&D investment's risk and effectiveness.

This paper has two main contributions. First, it contributes to the literature on the relation between R&D investment and stock returns (see, e.g., Lev and Sougiannis, 1996; Chan, Lakonishok, and Sougiannis, 2001; Chambers, Jennings, and Thompson, 2002; Eberhart, Maxwell, and Siddique, 2004; Hsu, 2009; Bena and Garlappi, 2011; Li, 2011; Lin, 2012; Hirshleifer, Hsu, and Li, 2013; Cohen, Diether, and Malloy, 2013). Prior studies find positive premiums associated with R&D-intensity measures. Hou, Xue, and Zhang (2014, 2015) show that their q-factor model can capture many anomalies in the cross section but not the R&D-to-market (i.e., R&D expenditure scaled by market equity) anomaly. Thus, a thorough understanding of the R&D anomaly is still lacking, and this gap motivates my work. By accounting for the rival risk associated with R&D projects, I numerically illustrate and empirically show that the positive R&D-return relation is more pronounced for firms in competitive industries. Furthermore, the role of competition cannot be justified by financial constraints and innovation ability, both of which are proposed as explanations for the R&D anomaly. Hence, these pieces of evidence suggest that competition independently drives a significant portion of the positive R&D-return relation.

Second, this paper contributes to the literature on the relation between competition and stock returns (see, e.g., Hou and Robinson, 2006; Aguerrevere, 2009). Hou and Robinson

(2006) find that competitive industries outperform concentrated industries by earning higher average returns. Using a real options model, Aguerrevere (2009) shows that the relation between competition and returns varies with product market demand, which affects the relative riskiness of assets in place and growth options. By taking into account competition's significant impact on R&D-intensive projects, I not only propose an alternative mechanism through which competition affects a firm's risk dynamics, but also show a robust empirical relation between competition and returns among firms with aggressive R&D inputs.

The rest of the paper proceeds as follows. Section 2 describes the model and develops the testable hypotheses. Section 3 provides details regarding the data sources and variable definitions. Section 4 presents the empirical results. Finally, Section 5 concludes.

2. Hypotheses development

To study the interaction effect of product market competition and R&D investment, I adopt the partial equilibrium model developed by Berk, Green, and Naik (2004) for a single multistage R&D venture. A brief overview of the model is provided prior to the derivation of two testable hypotheses.

2.1. Overview of the model

In the model, the firm operates in continuous time and progresses through the R&D project in sequential stages. It receives a stream of stochastic cash flows after it successfully completes N discrete stages. At any time prior to completing the project, the manager must make investment decisions to maximize the firm's value. If the firm decides to continue the project, it must incur an investment cost. While the R&D cost can be a known function of the number of completed stages, $n(t)$, I set it as a constant over all stages for simplicity's sake. This cost is expressed as RD. The investment level is not a choice variable.

Competition or obsolescence risk is modeled by the obsolescence rate, ϕ, which is the fixed probability that the potential or actual cash flow is extinguished over the next instant. In the model, this risk is idiosyncratic and thus does not demand a risk premium itself. However, a high probability of obsolescence indicates a high likelihood that the potential cash flows will become zero. Thus, a high obsolescence rate reduces the benefits of R&D investing and in turn the value of the option to continue the project. Therefore, the obsolescence rate affects the firm's decision whether to either continue or suspend the project and thus indirectly affects its systematic risk and risk premium.

In competitive industries, many firms are competing to develop a new product or technology. When one firm claims victory, that firm takes the market share. Other firms must then face a project with zero future cash flows and either suspend or abandon the R&D project. In contrast, in concentrated industries, there are fewer competitors, and firms can engage in R&D projects with less fear regarding rivals' breakthroughs. Therefore, ϕ tends to be higher in competitive industries.

2.2. Valuation

After the firm successfully completes N discrete stages, it receives a stream of stochastic cash flows, denoted $c(t)$, which follows a geometric Brownian motion:

$$dc(t) = \mu c(t)\,dt + \sigma c(t)\,dw(t), \tag{1}$$

where μ is the constant growth rate of cash flows, σ is the constant standard deviation of cash flows, and $dw(t)$ is an increment of a Wiener process.

The partial equilibrium model adopts an exogenous pricing kernel, which is given by the following process:

$$dm(t) = -rm(t)\,dt - \theta m(t)\,dz(t), \tag{2}$$

where r is the constant risk-free rate, and the risk premium for the cash flow process $c(t)$ is denoted as

$$\lambda = \sigma\theta\rho, \tag{3}$$

where ρ is the correlation between the Brownian motion processes $w(t)$ and $z(t)$.

Under the risk-neutral measure, the cash flow process $c(t)$ follows a geometric Brownian motion:

$$dc(t) = \hat{\mu} c(t)\,dt + \sigma c(t)\,d\hat{w}(t), \tag{4}$$

where $\hat{w}(t)$ is a Brownian motion under the risk-neutral measure and $\hat{\mu} = \mu - \lambda$ is the constant drift term of the cash flow process under the risk-neutral measure.

When deciding whether to continue investing, the firm's manager observes the number of completed stages, $n(t)$; the level of cash flow that the project would be producing if the project were completed; and whether or not the firm's potential cash flow has been extinguished through obsolescence. If the cash flow is extinguished, then the firm value becomes zero. Because other key variables, such as success intensity and investment cost, are assumed to be known functions of $n(t)$, albeit conditional on the project remaining in operation, the firm value at time t depends on the future cash flow, $c(t)$, and the number of completed stages, $n(t)$. The firm value at time t is thus denoted by $V(c(t), n(t))$. For simplicity' sake, this value is expressed as $V(c, n)$ hereafter.

If the project is completed successfully, then the firm receives a stream of stochastic cash flows. Consequently, at that point, the firm value is simply the continuous-time version of the Gordon and Williams growth model. At any time t prior to the project's completion, the firm value is the maximum of the firm's risk-neutral expected discounted future value at time T (i.e., an arbitrary point in the future) plus the discounted value of any cash flows received from time t to T. Thus, this multistage investment problem is given as

$$V(c,n) = \max_{u(s)\in\{0,1\}, s\in(t,T)} \mathrm{E}_t^Q \Big\{ e^{-(r+\phi)(T-t)} V(c(T), n(T)) + \int_t^T e^{-(r+\phi)(s-t)} (\nu(s)c(s) - u(s)RD)\,ds \Big\}, \tag{5}$$

where u denotes the decision variable, with $u=1$ if the firm continues investing over the next instant and zero otherwise, and $\mathrm{E}^Q[\,]$ is the expectation operator under the risk-neutral (pricing) measure, Q. ν is an indicator variable that takes a value of zero or one to indicate whether the project is completed. $\nu=1$ indicates that the project is completed and that $n(t)=N$. $\nu=0$ indicates that the project is not completed and that $n(t)<N$.

The Hamilton-Bellman-Jacobi equation of the investment problem can be derived by applying Ito's lemma to the value function, $V(c,n)$. The equation is given as

$$(r+\phi)V(c,n)=\frac{1}{2}\sigma^2c^2\frac{\partial^2}{\partial c^2}V(c,n)+\hat{\mu}c\frac{\partial}{\partial c}V(c,n)+\max_{u\in\{0,1\}} u\pi[V(c,n+1)-V(c,n)]-RD, \quad (6)$$

where π denotes the probability that the firm will successfully complete the current stage over the next instant if the firm invests in the project. In the simplified case examined in Berk, Green, and Naik (2004), π is a known function of $n(t)$. For simplicity, I assume that π is a constant over all stages and, thus, write it as π hereafter. Once the project successfully advances to the next stage, the firm value will increase to $V(c,n+1)$. Thus, $\pi[V(c,n+1)-V(c,n)]$ is the expected increase in firm value after the investment (i.e., the benefit of R&D investing).

At each time, the firm makes an investment decision. If the future cash flow exceeds the threshold, $c^*(n)$, then the firm will invest in the project and $u=1$. If the future cash flow is below the threshold, $c^*(n)$, then the firm will suspend the project and $u=0$. These are denoted as the continuation and mothball regions, respectively. The analytical solution of the Hamilton-Bellman-Jacobi equation can be derived by specifying the form of its function in both the continuation and mothball regions and by then applying standard boundary conditions at the cash flow threshold. Berk, Green, and Naik (2004) provide detailed derivations regarding the solution to this equation, and I reproduce these derivations in the Internet Appendix.

The risk premium of the R&D venture at stage n, $R(n)$, can be computed as

$$R(n)=\frac{(\partial V(c,n)/\partial c)c}{V(c,n)}\lambda. \quad (7)$$

After the project is completed, no further investment decision is required. The venture is equivalent to a traditional cash-producing project that demands the same risk premium λ as the stochastic cash flow process. In the mothball region, the firm, prior to the project's completion, is equivalent to an option to invest in the R&D project. The firm is thus riskier than the underlying cash flow because of the implicit leverage feature of options. In the continuation region, meanwhile, the firm consists of an option to suspend the project, the expected R&D cost when investing, and the discounted value of its future cash flow. Thus, the firm is less risky in the continuation region than in the mothball region and riskier than the underlying cash flow. In the following subsections, I develop hypotheses to show the relation of an R&D firm's risk premium, $R(n)$, with its investment level, RD, and the obsolescence rate, ϕ.

2.3. R&D investment and risk premium

At any time prior to the project's completion, the firm must make an investment decision. If the future cash flow is below a certain threshold, then the firm will suspend the project. A firm that must overcome a higher cash flow threshold to continue the project is riskier because a high cash flow threshold increases the chance that the project will be suspended if an adverse shock to the future cash flow occurs. Therefore, the firm's investment decision and value are more sensitive to the systematic risk that the cash flow carries.

A higher R&D investment requirement tends to lower the value of the option to continue the project, thereby raising the cash flow threshold that the firm needs to overcome. Therefore, a higher R&D investment requirement leads to a higher risk premium. In other words, firms with aggressive R&D investments have high expected returns. Furthermore, the positive relation between R&D investment and expected returns is stronger for firms in industries with higher obsolescence rates (i.e., competitive industries), for a high obsolescence rate further raises a firm's cash flow threshold. Hence, the investment decisions and value of R&D-intensive firms in competitive industries are more sensitive to the systematic risk that the cash flow carries.

This line of argument yields the first hypothesis. This hypothesis is not proven analytically. Instead, I show the hypothesis with numerical examples.

Hypothesis 1. In the continuation region where cash flow $c\geq c^*(n)$,

$$\frac{\partial R(n)}{\partial RD}>0 \quad (8)$$

and

$$\frac{\partial^2 R(n)}{\partial RD\partial\phi}>0. \quad (9)$$

To appreciate these effects visually, I numerically show these relations using an R&D venture that requires five stages to be completed. The same parameter values are adopted as those used by Berk, Green, and Naik (2004): The risk-free rate, r, is 7% per year; the drift, μ, and the standard deviation, σ, of the cash flow process are 3% and 40%, respectively; the risk premium for the cash flow process, λ, is 8% per year; and the success intensity, π, is 2.0, which is equivalent to a 86% probability of successfully completing one stage in a year.[1] My results are robust to the variation in success intensity with each additional completed stage. For example, in one of the unreported cases, I set the value of π in an increasing manner. In other words, π begins with a low value and increases by 0.2 as the project advances to the next stage. Nonetheless, the results still hold. In addition, the obsolescence rate ϕ ranges from 0.05 to 0.25 cross-sectionally, and the required R&D investment is 5.0 for firms with low R&D inputs and 25.0 for firms with high R&D inputs.[2]

[1] If $N(t)$ denotes the number of events that occurred before time t and follows a Poisson distribution, then the probability that k events occurred during the time interval $[t,t+\tau]$ is $P[N(t+\tau)-N(t)=k]=\frac{e^{-\lambda\tau}(\lambda\tau)^k}{k!}$. Thus, $P[N(t+\tau)-N(t)>0]=1-e^{-\lambda\tau}$. If $\tau=1$ and $\lambda=2$, then the probability of completing at least one stage in a year is $1-e^{-2}=0.86$.

[2] If $N(t)$ denotes the number of events that occurred before time t and follows a Poisson distribution, then the probability that k events occurred during the time interval $[t,t+\tau]$ is $P[N(t+\tau)-N(t)=k]=\frac{e^{-\lambda\tau}(\lambda\tau)^k}{k!}$. Thus, $P[N(t+\tau)-N(t)=0]=e^{-\lambda\tau}$. If $\tau=1$ and $\lambda=\phi$, then the probability of surviving one year without obsolescence is $e^{-\phi}$. The range of ϕ from 0.05 to 0.25 corresponds to a surviving probability range of 0.77 to 0.95.

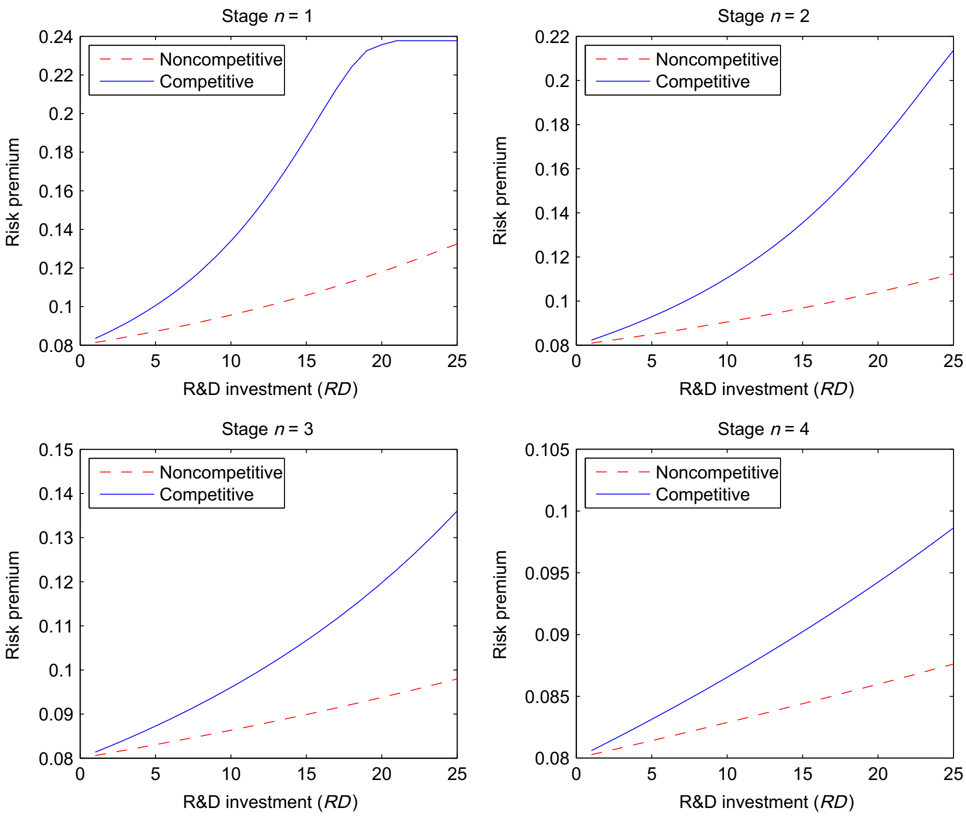

Fig. 1. Research and development (R&D) investment and risk premium. This figure plots the annual risk premium of a venture that needs to complete five stages against the R&D investment requirement (RD) for firms in competitive and noncompetitive industries (as measured by the obsolescence rate, ϕ) and over different stages. The top left plot is for projects that have completed the first stage ($n=1$), the top right plot is for projects that have completed the first two stages ($n=2$), the bottom left plot is for projects that have completed three stages ($n=3$), and the bottom right plot is for projects that have completed four stages ($n=4$). The solid and dashed lines correspond to two different obsolescence rates (ϕ): 0.05 for concentrated industries and 0.25 for competitive industries. The parameters in the model are set as follows: The risk-free rate, r, is 7% per year; the annual drift, μ, and the standard deviation, σ, of the cash flow process are 3% and 40%, respectively; the risk premium for the cash flow process, λ, is 8% per year; and the success intensity, π, is 2.0, which is equivalent to a 86% probability of successfully completing one stage in a year.

Fig. 1 plots firms' risk premiums against their R&D investment requirements (RD) for different obsolescence rates (i.e., different degrees of competition) and for different stages prior to the project's completion. The horizontal sections in the plots correspond to the mothball regions, where cash flows are lower than the thresholds. As R&D investment increases, the cash flow threshold increases, making it more likely for firms to suspend the project.

As shown in the plots, R&D investment is positively related to the risk premium in the continuation region, and this positive relation holds for all stages of the R&D venture. More important, the positive R&D-return relation is much stronger for firms in competitive industries. In addition, the positive relation weakens as the project approaches completion. As shown in the bottom right plot, when $n=4$, the magnitude of the risk premium is much smaller than that in earlier stages. This smaller magnitude occurs because a firm's value increases as more stages are completed. In turn, this increased firm value reduces the chance of project suspension.

The same pattern is obtained when the risk premium averaged over all stages of the project is plotted against R&D investment requirement. This figure is available in the Internet Appendix. More important, the propositions of this hypothesis are consistent with the empirical findings.

2.4. Competition and risk premium

A high obsolescence rate leads to a high probability that the potential or actual future cash flows will be extinguished, thereby reducing the benefits of continuing the R&D investment. Therefore, firms in industries with higher obsolescence rates need to pass higher cash flow thresholds to continue R&D projects. As a result, such firms have higher risk premiums. In other words, firms in competitive industries have higher expected returns. Moreover, this positive relation is stronger among firms with aggressive R&D inputs, which are also positively associated with the cash flow thresholds. This insight yields the second hypothesis.[3]

Hypothesis 2. In the continuation region where cash flow $c \geq c^*(n)$,

$$\frac{\partial R(n)}{\partial \phi} > 0 \tag{10}$$

[3] Eq. (11) in Hypothesis 2 is essentially the same as Eq. (9) in Hypothesis 1. The same equation is used in two different hypotheses because there are two fundamental relations in the paper (i.e., the R&D-return relation and the competition-return relation), and I would like to illustrate the properties of these two relations separately.

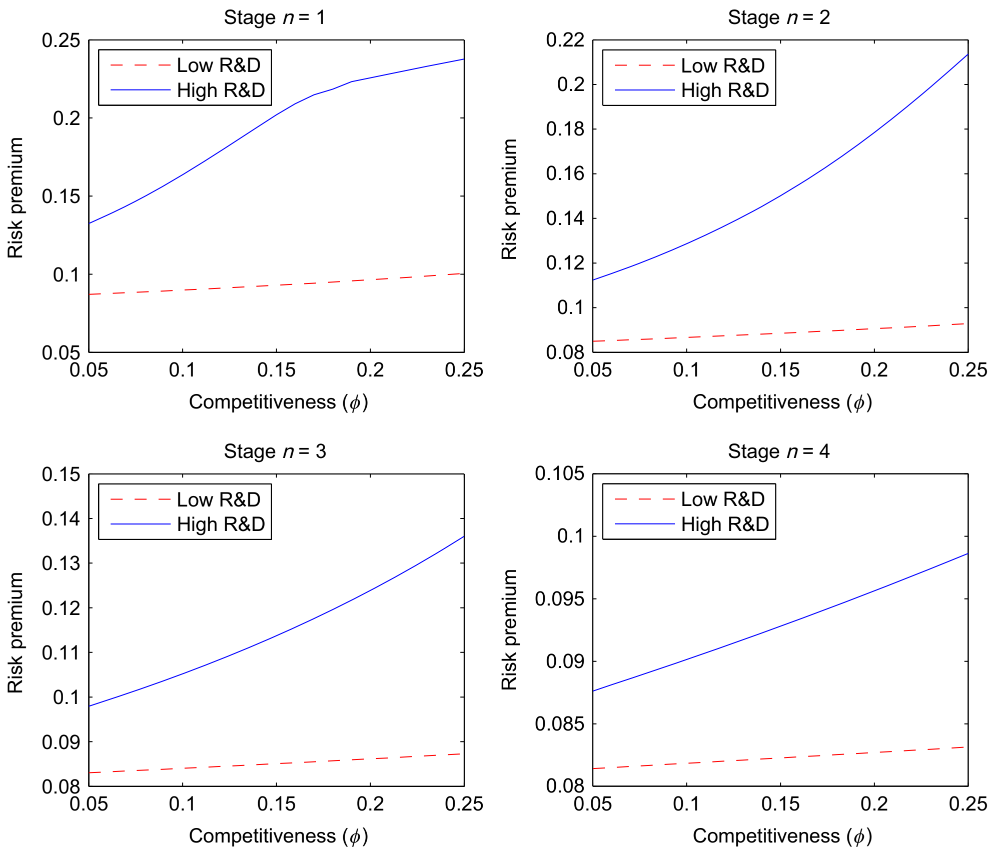

Fig. 2. Competition and risk premium. This figure plots the annual risk premium of a venture that needs to complete five stages against the obsolescence rate (ϕ) for firms with different research and development (R&D) investment requirements (RD). The top left plot is for projects that have completed the first stage ($n=1$), the top right plot is for projects that have completed two stages ($n=2$), the bottom left plot is for projects that have completed three stages ($n=3$), and the bottom right plot is for projects that have completed four stages ($n=4$). The dashed and solid lines correspond to two different R&D investment requirements (RD): 5 for low R&D firms and 25 for high R&D firms. The parameters in the model are set as follows: The risk-free rate, r, is 7% per year; the annual drift, μ, and the standard deviation, σ, of the cash flow process are 3% and 40%, respectively; the risk premium for the cash flow process, λ, is 8% per year; and the success intensity, π, is 2.0, which is equivalent to a 86% probability of successfully completing one stage in a year.

and

$$\frac{\partial^2 R(n)}{\partial\phi\partial RD} > 0. \tag{11}$$

As with Hypothesis 1, I use numerical examples to illustrate the propositions in Hypothesis 2. Fig. 2 plots firms' risk premiums against the obsolescence rates for different levels of R&D investment requirements and for different project stages. The positive competition-return relation clearly prevails in each subplot of the figure, and the relation is much more pronounced among firms with aggressive R&D investments. Furthermore, a similar relation is obtained when plotting the risk premium averaged over different stages of the project against the obsolescence rate. More important, the propositions of this hypothesis are also consistent with the empirical results.

To determine if the risk premium patterns in the numerical examples hold when different parameter values are used, I vary the value of the parameters in the model by 50% and obtain consistent results. In addition, in the case in which the observations of R&D investment requirement and obsolescence rate are jointly drawn from the same distribution, similar numerical results are found.[4]

In sum, the hypotheses that the positive R&D-return relation prevails in competitive industries and that the positive competition-return relation is stronger among R&D-intensive firms follow directly from the Berk, Green, and Naik (2004) framework for analyzing R&D return dynamics. In the following sections, a standard portfolio sorting approach is used to test the model's predictions.

3. Data

Firms' monthly stock returns and accounting information are obtained from the Center for Research in Security Prices (CRSP) and the Compustat Annual Industrial Files for the period from 1963 to 2013. To be included in the sample, a firm must have matching data in both data sets. Following Fama and French (1992), only NYSE-, Amex-, and Nasdaq-listed securities with share codes 10 and 11

[4] These results are available in the Internet Appendix.

are included in the sample. Thus, only firms with ordinary common equity are included (American depositary receipts, real estate investment trusts, and units of beneficial interest are excluded). Finally, firms in financial and regulated industries are excluded.

To ensure that the accounting information is already incorporated into firms' stock returns, I follow Fama and French (1992) to match accounting information for all fiscal year-ends in calendar year $t-1$ with CRSP stock return data from July of year t to June of year $t+1$. Thus, a half-year gap at minimum exists between the fiscal year-end and the stock return, which provides a certain period of time for the accounting information to be incorporated into stock prices. However, firms have different fiscal year-ends. Thus, the time gap between the accounting data and matching stock returns varies across firms.

Throughout this paper, R&D intensity is measured by R&D expenditure scaled by market equity (RD/ME). Hou, Xue, and Zhang (2014, 2015) show that RD/ME forecasts returns, but that other measures of R&D intensity (e.g., RD/Sales and RD capital/Assets) fail to produce significant high-minus-low decile returns, on average, at the 5% level with NYSE breakpoints and value-weighted returns, as well as with all-but-micro breakpoints and equal-weighted returns. These authors' finding underscores the need to understand this R&D-to-market anomaly more fully. Therefore, using RD/ME to measure R&D intensity in this paper is more meaningful.

Product market competition is measured by the Herfindahl-Hirschman Index (HHI), a measure that is commonly used by researchers in the literature on industrial organization.[5] The Herfindahl Index is defined as the sum of squared market shares:

$$\mathrm{HHI}_{jt} = \sum_{i=1}^{N_j} s_{ijt}^2, \tag{12}$$

where s_{ijt} is the market share of firm i in industry j in year t, N_j is the number of firms in industry j in year t, and HHI_{jt} is the Herfindahl Index of industry j in year t. The market share of an individual firm is calculated by using the firm's net sales (Compustat annual item SALE) divided by the total sales value of the entire industry.[6] Following Hou and Robinson (2006), I classify industries with three-digit standard industrial classification codes from CRSP, and all firms with non-missing sales value are included in the sample to calculate the Herfindahl Index for a particular industry.[7] The calculation is performed every year, and the average value over the past two years is used as the Herfindahl Index of an industry to prevent potential data errors in the analysis. Hoberg and Phillips (2010) construct an alternative Herfindahl Index using a sample that includes both public and private firms. Hence, as a robustness check, I also perform the double-sorting test using this alternative Herfindahl Index.

4. Results

This section presents my main empirical findings and the test results on alternative explanations for the R&D-return relation.

4.1. Interaction effect between R&D investment and product market competition

In this subsection, I investigate the positive interaction effect between product market competition and R&D investment by using a conventional double-sorting approach. In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups based on the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of Herfindahl Index in year $t-1$. Meanwhile, independently, firms with non-missing R&D value are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of RD/ME from the previous year.[8] This procedure results in nine portfolios with different characteristics in terms of the degree of competition and R&D intensity.

Microcap firms, because of their small size, tend to have higher R&D intensity and, accordingly, are assigned to R&D-intensive groups. This obscures the interpretation of the return on the R&D-intensive portfolio. To minimize the impact of microcap firms, I adopt the empirical design in Hou, Xue, and Zhang (2014, 2015) to construct the breakpoints for R&D intensity. First, I use firms traded in NYSE to calculate breakpoints for R&D intensity, after which I apply the breakpoints to all stocks in the sample and then report the value-weighted portfolio returns. Second, after excluding stocks with market equity below the 20th NYSE percentile, I then use the remaining NYSE, Amex, and Nasdaq stocks to calculate breakpoints and report the equal-weighted portfolio returns. In the tables, I use NYSE breakpoints and all-but-micro breakpoints to represent these two breakpoints construction methods.

Monthly equal-weighted or value-weighted returns on the nine portfolios are calculated for the period from July of year t to June of year $t+1$, and the portfolios are rebalanced in June of each year. Further, the Carhart (1997) four-factor model, the Hou, Xue, and Zhang (2015) q-factor model, and the Fama and French (2015) five-factor model are used to account for style or risk differences among the portfolios. I estimate the following model specifications:

$$R_t = \alpha + \beta_1 \times \mathrm{MKT}_t + \beta_2 \times \mathrm{SMB}_t + \beta_3 \times \mathrm{HML}_t + \beta_4 \times \mathrm{UMD}_t + \epsilon_t, \tag{13}$$

[5] See, e.g., Hou and Robinson (2006) and Giroud and Mueller (2011). The use of the Herfindahl Index to measure product market competition is also supported by theory (i.e., Tirole, 1988).

[6] By using the same procedure, the Herfindahl Index can be constructed with firms' asset or equity data. These alternative measures produce qualitatively similar results.

[7] On the one hand, an extremely fine-grained industry classification results in statistically unreliable portfolios. On the other hand, if the classification is not sufficiently fine-grained, then firms in different lines of business are grouped together.

[8] Sorting these two measures based on quintile breakpoints produces qualitatively similar, and sometimes stronger, results. The tables are available in the Internet Appendix.

Table 1
Research and development (R&D)-return relation in competitive and concentrated industries.

This table reports the monthly raw returns and abnormal returns (α, in percent) on portfolios sorted on product market competition and R&D intensity. Product market competition is measured by the Herfindahl-Hirschman Index (HHI), which is computed based on the market share of each firm in the industry. The detailed definition is provided in Section 3. R&D intensity is defined as R&D expenditure scaled by market equity (RD/ME). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year $t-1$. Independently, firms with non-missing R&D are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of RD/ME in year $t-1$. Monthly returns on the resulting nine portfolios are then calculated from July of year t to June of year $t+1$. Monthly portfolio abnormal returns are computed by running time series regression of portfolio excess returns on risk factors in the Carhart (1997) four-factor model, the Hou, Xue, and Zhang (2015) q-factor model, and the Fama and French (2015) five-factor model. In Panel A, I use NYSE breakpoints for R&D intensity and report the value-weighted portfolio returns. In Panel B, I exclude stocks with market equity below the 20th NYSE percentile, use the remaining stocks to calculate breakpoints for R&D intensity, and then report the equal-weighted portfolio returns. The sample period is from July 1963 to December 2013. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	Low competition				High competition			
	$R\&D_L$	$R\&D_M$	$R\&D_H$	H − L	$R\&D_L$	$R\&D_M$	$R\&D_H$	H − L
Panel A: NYSE breakpoints and value-weighted returns								
Raw return	1.17***	0.86***	0.99***	−0.18	0.82***	1.02***	1.40***	0.58***
	(5.61)	(4.17)	(4.09)	(0.65)	(4.32)	(5.22)	(5.63)	(3.15)
Carhart four-factor α	0.20	−0.02	−0.04	−0.24	0.00	0.29***	0.39***	0.39**
	(0.87)	(0.15)	(0.20)	(1.05)	(0.03)	(4.18)	(3.56)	(2.32)
HXZ q-factor α	0.15	−0.26	−0.14	−0.29	0.04	0.32***	0.54***	0.50***
	(0.79)	(1.48)	(0.64)	(0.98)	(0.33)	(3.94)	(4.44)	(2.72)
Fama and French five-factor α	0.10	−0.25	−0.35	−0.45	0.05	0.33***	0.44***	0.39**
	(1.61)	(1.65)	(1.66)	(1.33)	(0.47)	(4.64)	(3.92)	(2.28)
Panel B: All-but-micro breakpoints and equal-weighted returns								
Raw return	1.12***	0.96***	1.10***	−0.02	0.92***	1.13***	1.51***	0.59***
	(5.00)	(4.59)	(3.96)	(0.20)	(3.63)	(4.47)	(4.84)	(3.77)
Carhart four-factor α	0.18	0.02	−0.10	−0.28	−0.04	0.26***	0.46***	0.50***
	(1.31)	(0.19)	(0.53)	(1.34)	(0.43)	(3.56)	(3.95)	(3.41)
HXZ q-factor α	−0.06	−0.18	0.07	0.13	0.10	0.48***	0.77***	0.67***
	(0.38)	(1.24)	(0.34)	(0.56)	(0.92)	(5.17)	(5.70)	(4.03)
Fama and French five-factor α	−0.02	−0.16	−0.39**	−0.37	−0.12	0.30***	0.47***	0.59***
	(0.17)	(1.31)	(2.00)	(1.66)	(1.18)	(3.61)	(3.69)	(4.00)

$$R_t = \alpha + \beta_1 \times \mathrm{MKT}_t + \beta_2 \times r_{\mathrm{ME}_t} + \beta_3 \times r_{\mathrm{I/A}_t} + \beta_4 \times r_{\mathrm{ROE}_t} + \epsilon_t, \quad (14)$$

and

$$R_t = \alpha + \beta_1 \times \mathrm{MKT}_t + \beta_2 \times \mathrm{SMB}_t + \beta_3 \times \mathrm{HML}_t + \beta_4 \times \mathrm{RMW}_t + \beta_5 \times \mathrm{CMA}_t + \epsilon_t, \quad (15)$$

where R_t is the monthly excess return of a portfolio and MKT_t is the value-weighted market return minus the risk-free rate in month t. SMB_t, HML_t, and UMD_t are the month t size factor, book-to-market factor, and momentum factor, respectively, in the Carhart (1997) four-factor model. r_{ME_t}, $r_{\mathrm{I/A}_t}$, and r_{ROE_t} represent the month t size factor, investment factor, and profitability factor, respectively, in the Hou, Xue, and Zhang (2015) q-factor model. RMW_t and CMA_t are the month t profitability factor and investment factor, respectively, in the Fama and French (2015) five-factor model.[9] SMB_t and HML_t factors are downloaded from Kenneth R. French's online data library, and the UMD_t factor is constructed according to Carhart (1997).[10]

Table 1 reports the monthly raw returns and abnormal returns (i.e., alpha in the asset pricing model) on R&D-intensity portfolios in competitive (i.e., bottom 30% of the HHI distribution) and concentrated (i.e., top 30% of the HHI distribution) industries. In Panel A, I use NYSE breakpoints for R&D intensity and report value-weighted portfolio returns. In Panel B, I use all-but-micro breakpoints and report equal-weighted portfolio returns.

With respect to findings, first, the return on the high-minus-low R&D-intensity portfolio is positive and significant in competitive industries and is negative and insignificant in concentrated industries. For example, when analyzed using NYSE breakpoints, the monthly value-weighted return to the high-minus-low R&D-intensity portfolio in competitive industries is 0.58% and statistically significant at the 1% level. In contrast, this return is −0.18% with a t-statistic of 0.65 in concentrated industries. Similarly, when analyzed using all-but-micro breakpoints, the monthly equal-weighted return on the high-minus-low R&D-intensity portfolio is 0.59% with

[9] I thank Chen Xue for sharing the time series of the factors in the Hou, Xue, and Zhang (2015) q-factor model. I also thank Kenneth R. French for sharing the time series of the RMW and CMA factors in the Fama and French (2015) five-factor model.

[10] The address of the data library is http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 2

Competition-return relation among research and development (R&D)-intensive and R&D-weak firms.

This table reports the monthly raw returns and abnormal returns (α, in percent) on portfolios sorted on product market competition and R&D intensity. Product market competition is measured by the Herfindahl-Hirschman Index (HHI), which is computed based on the market share of each firm in the industry. The detailed definition is provided in Section 3. R&D intensity is defined as R&D expenditure scaled by market equity (RD/ME). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year $t-1$. Independently, firms with non-missing R&D are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of RD/ME in year $t-1$. Monthly returns on the resulting nine portfolios are then calculated from July of year t to June of year $t+1$. Monthly portfolio abnormal returns are computed by running time series regression of portfolio excess returns on risk factors in the Carhart (1997) four-factor model, the Hou, Xue, and Zhang (2015) q-factor model, and the Fama and French (2015) five-factor model. In Panel A, I use NYSE breakpoints for R&D intensity and report the value-weighted portfolio returns. In Panel B, I exclude stocks with market equity below the 20th NYSE percentile, use the remaining stocks to calculate breakpoints for R&D intensity, and then report the equal-weighted portfolio returns. The sample period is from July 1963 to December 2013. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	Low R&D intensity				High R&D intensity			
	HHI_H	HHI_M	HHI_L	L−H	HHI_H	HHI_M	HHI_L	L−H
Panel A: NYSE breakpoints and value-weighted returns								
Raw return	1.17***	0.77***	0.82***	−0.35	0.99***	1.12***	1.40***	0.41
	(5.61)	(3.63)	(4.32)	(1.05)	(4.09)	(4.63)	(5.63)	(1.67)
Carhart four-factor α	0.20	−0.13	0.00	−0.20	−0.04	−0.06	0.39***	0.43*
	(0.87)	(1.19)	(0.03)	(1.34)	(0.20)	(0.43)	(3.56)	(1.88)
HXZ q-factor α	0.15	−0.20	0.04	−0.11	−0.14	−0.17	0.54***	0.68***
	(0.79)	(1.58)	(0.33)	(0.49)	(0.64)	(1.08)	(4.44)	(2.79)
Fama and French five-factor α	0.10	−0.23**	0.05	−0.05	−0.35	−0.23*	0.44***	0.79***
	(1.61)	(2.03)	(0.47)	(1.67)	(1.66)	(1.75)	(3.92)	(3.57)
Panel B: All-but-micro breakpoints and equal-weighted returns								
Raw return	1.12***	0.95***	0.92***	−0.20	1.10***	1.35***	1.51***	0.41**
	(5.00)	(3.83)	(3.63)	(1.49)	(3.96)	(4.92)	(4.84)	(2.01)
Carhart four-factor α	0.18	−0.14	−0.04	−0.22	−0.10	0.09	0.46***	0.56***
	(1.31)	(1.26)	(0.43)	(1.52)	(0.53)	(0.79)	(3.95)	(2.66)
HXZ q-factor α	−0.11	−0.21***	−0.25	−0.14	0.07	0.02	0.77***	0.70***
	(0.38)	(2.79)	(0.92)	(1.09)	(0.34)	(0.11)	(5.70)	(2.86)
Fama and French five-factor α	−0.02	−0.42***	−0.12	−0.10	−0.39**	−0.10	0.47***	0.86***
	(0.17)	(4.03)	(1.18)	(0.68)	(2.00)	(0.81)	(3.69)	(4.15)

a t-statistic of 3.77 in competitive industries, but this return is only −0.02% and insignificant in concentrated industries.

Second, as shown in both panels, the abnormal returns on R&D-intensity portfolios increase monotonically with R&D intensity for firms in competitive industries, and these estimates are small (frequently negative) and insignificant for firms in concentrated industries. This finding holds for both NYSE breakpoints and all-but-micro breakpoints, as well as for all three asset pricing models. For instance, Panel A shows that the monthly value-weighted q-factor alphas on the low, medium, and high R&D-intensity portfolios in competitive industries are 0.04%, 0.32%, and 0.54%, with t-statistics of 0.33, 3.94, and 4.44, respectively. The alpha on the high-minus-low R&D-intensity portfolio is 50 basis points per month (t-statistic=2.72), which translates to 600 basis points annually. In contrast, the corresponding estimates in concentrated industries are 0.15%, −0.26%, and −0.14%, with t-statistics of 0.79, 1.48, and 0.64, respectively. The alpha on the high-minus-low R&D-intensity portfolio is negative (−0.29%) and insignificant (t-statistic=0.98). Moreover, the Carhart four-factor alpha and the Fama and French five-factor alpha on the high-minus-low R&D-intensity portfolio in competitive industries are 0.39% and 0.39%, with t-statistics of 2.32 and 2.28, respectively, and these estimates in concentrated industries are −0.24% and −0.45%, with t-statistics of 1.05 and 1.33, respectively.

Panel B shows stronger return patterns. The monthly equal-weighted q-factor alphas on the low, medium, and high R&D-intensity portfolios in competitive industries are 0.10%, 0.48%, and 0.77%, with t-statistics of 0.92, 5.17, and 5.70, respectively. The alpha on the high-minus-low R&D-intensity portfolio is as high as 67 (t-statistic=4.03) basis points per month, which translates to an annual premium of almost 8%, and is larger than the corresponding estimate in Panel A. In contrast, the alpha on the high-minus-low R&D-intensity portfolio in concentrated industries is only 0.13% and insignificant (t-statistic=0.56). Moreover, the Carhart four-factor alpha and the Fama and French five-factor alpha on the high-minus-low R&D-intensity portfolio in competitive industries are also larger than the corresponding estimates in Panel A: 0.50% and 0.59%, with t-statistics of 3.41 and 4.00, respectively.

The portfolios are rebalanced every year in the analysis because the variables used to form the portfolios are updated annually. Thus, the transaction costs associated with the trading strategy are low, and the return spread after adjusting for the transaction costs remains economically large.

To summarize, the double-sorted portfolio results in Table 1 support the hypothesis that the positive R&D-

return relation manifests itself in competitive industries. Interestingly, I find that the R&D premium disappears, or even becomes negative, for firms in concentrated industries. This finding suggests that the positive R&D-return relation identified in prior studies is an average effect of firms from industries with different degrees of competition. Moreover, given that R&D-intensive firms in competitive industries earn positive and significant abnormal returns and R&D-intensive firms in concentrated industries earn no or even negative abnormal returns, engaging in aggressive R&D activities likely, but not absolutely, affects firms' risk profiles and expected returns. These effects can be significantly different for firms with the same level of R&D intensity but operating in industries with different market structures. Therefore, competition explains a significant portion of the R&D premium.

Next, I test the second hypothesis that the positive competition-return relation is stronger among R&D-intensive firms. Table 2 reports the monthly raw returns and abnormal returns on competition portfolios among R&D-intensive (i.e., top 30% of the R&D intensity distribution) and R&D-weak (i.e., bottom 30% of the R&D intensity distribution) firms. In Panels A and B, NYSE breakpoints and all-but-micro breakpoints are used for R&D intensity, respectively.

With respect to findings, first, when analyzed using all-but-micro breakpoints, the return on the high-minus-low competition portfolio is positive and significant for the R&D-intensive group and is negative and insignificant for the R&D-weak group. The monthly equal-weighted return on the high-minus-low competition portfolio is 0.41% and statistically significant at the 5% level for the R&D-intensive group. In contrast, this return is −0.20% with a t-statistic of 1.49 for the R&D-weak group. In addition, when analyzed using NYSE breakpoints, the monthly value-weighted return on the high-minus-low competition portfolio for the R&D-intensive group has a similar magnitude to the corresponding estimate in Panel B, although it is not statistically significant.

Second, as shown in both panels, firms in competitive industries outperform firms in concentrated industries by earning higher abnormal returns over the sample period. However, this pattern holds only for firms in the R&D-intensive group. The abnormal return on the high-minus-low competition portfolio is small and even negative, in most cases, for firms in the R&D-weak group. This finding is robust for all three asset pricing models, as well as for both NYSE breakpoints and all-but-micro breakpoints. For example, in Panel A, the monthly value-weighted q-factor alphas on the low, medium, and high competition portfolios for the R&D-

Table 3

Research and development (R&D)-return relation: alternative Herfindahl-Hirschman Index.

This table reports the monthly raw returns and abnormal returns (α, in percent) on portfolios sorted on product market competition and R&D intensity. Product market competition is measured by the Herfindahl-Hirschman Index (HHI) in Hoberg and Phillips (2010). R&D intensity is defined as R&D expenditure scaled by market equity (RD/ME). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year $t-1$. Independently, firms with non-missing R&D are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of RD/ME in year $t-1$. Monthly returns on the resulting nine portfolios are then calculated from July of year t to June of year $t+1$. Monthly portfolio abnormal returns are computed by running time series regression of portfolio excess returns on risk factors in the Carhart (1997) four-factor model, the Hou, Xue, and Zhang (2015) q-factor model, and the Fama and French (2015) five-factor model. In Panel A, I use NYSE breakpoints for R&D intensity and report the value-weighted portfolio returns. In Panel B, I exclude stocks with market equity below the 20th NYSE percentile, use the remaining stocks to calculate breakpoints for R&D intensity, and then report the equal-weighted portfolio returns. The sample period is from July 1963 to December 2013. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	Low competition				High competition			
	$R\&D_L$	$R\&D_M$	$R\&D_H$	H − L	$R\&D_L$	$R\&D_M$	$R\&D_H$	H − L
Panel A: NYSE breakpoints and value-weighted returns								
Raw return	0.91***	0.93***	0.87***	−0.04	0.74**	1.07***	1.29***	0.55**
	(4.03)	(4.44)	(3.72)	(1.15)	(2.32)	(3.74)	(3.63)	(2.24)
Carhart four-factor α	0.14	0.12	−0.30	−0.44	−0.23	0.21	0.24**	0.47*
	(0.68)	(1.20)	(1.65)	(1.52)	(1.42)	(1.27)	(2.18)	(1.75)
HXZ q-factor α	−0.05	0.11	−0.20	−0.15	−0.03	0.28**	0.48***	0.51**
	(0.25)	(0.55)	(0.98)	(0.49)	(0.21)	(2.27)	(2.71)	(1.99)
Fama and French five-factor α	−0.05	0.06	−0.44**	−0.39	−0.11	0.29*	0.31***	0.42*
	(0.26)	(0.30)	(2.32)	(1.31)	(0.68)	(1.81)	(2.57)	(1.85)
Panel B: All-but-micro breakpoints and equal-weighted returns								
Raw return	1.10***	0.83***	1.10***	0.00	0.86**	1.10***	1.56***	0.70***
	(3.84)	(3.25)	(4.19)	(0.20)	(2.40)	(2.99)	(3.54)	(2.98)
Carhart four-factor α	−0.19	−0.16	−0.11	0.08	−0.23	0.11	0.37**	0.60***
	(1.10)	(0.96)	(0.60)	(0.36)	(1.63)	(1.02)	(2.25)	(2.63)
HXZ q-factor α	−0.39**	−0.14	−0.07	0.32	0.00	0.45***	0.76***	0.76***
	(2.13)	(0.73)	(0.34)	(1.35)	(0.02)	(3.36)	(4.03)	(3.35)
Fama and French five-factor α	−0.54	−0.46	−0.42	0.12	−0.27	0.17	0.33*	0.60***
	(1.37)	(1.65)	(1.22)	(0.53)	(1.66)	(1.23)	(1.94)	(2.80)

Table 4
Competition-return relation: alternative Herfindahl-Hirschman Index.

This table reports the monthly raw returns and abnormal returns (α, in percent) on portfolios sorted on product market competition and research and development (R&D) intensity. Product market competition is measured by the Herfindahl-Hirschman Index (HHI) in Hoberg and Phillips (2010). R&D intensity is defined as R&D expenditure scaled by market equity (RD/ME). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year $t-1$. Meanwhile, independently, firms with non-missing R&D are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of RD/ME in year $t-1$. Monthly returns on the resulting nine portfolios are then calculated from July of year t to June of year $t+1$. Monthly portfolio abnormal returns are computed by running time series regression of portfolio excess returns on risk factors in the Carhart (1997) four-factor model, the Hou, Xue, and Zhang (2015) q-factor model, and the Fama and French (2015) five-factor model. In Panel A, I use NYSE breakpoints for R&D intensity and report the value-weighted portfolio returns. In Panel B, I exclude stocks with market equity below the 20th NYSE percentile, use the remaining stocks to calculate breakpoints for R&D intensity, and then report the equal-weighted portfolio returns. The sample period is from July 1963 to December 2013. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	Low R&D intensity				High R&D intensity			
	HHI_H	HHI_M	HHI_L	L−H	HHI_H	HHI_M	HHI_L	L−H
Panel A: NYSE breakpoints and value-weighted returns								
Raw return	0.91***	1.14***	0.74**	−0.17	0.87***	1.27***	1.29***	0.42*
	(4.03)	(4.62)	(2.32)	(1.05)	(3.72)	(4.40)	(3.63)	(1.72)
Carhart four-factor α	0.14	0.04	−0.23	−0.37	−0.30	0.00	0.24**	0.54**
	(0.68)	(0.32)	(1.42)	(1.48)	(1.65)	(0.02)	(2.18)	(2.17)
HXZ q-factor α	0.15	−0.05	−0.03	−0.18	−0.20	−0.19	0.48***	0.68**
	(0.25)	(1.40)	(0.21)	(0.07)	(0.98)	(1.05)	(2.71)	(2.52)
Fama and French five-factor α	−0.05	−0.14	−0.11	−0.06	−0.44**	−0.20	0.31**	0.75***
	(0.26)	(1.02)	(0.68)	(0.24)	(2.32)	(1.22)	(2.57)	(3.20)
Panel B: All-but-micro breakpoints and equal-weighted returns								
Raw return	1.10***	1.18***	0.86**	−0.24	1.10***	1.44***	1.56***	0.46**
	(3.84)	(4.09)	(2.40)	(1.09)	(4.19)	(4.15)	(3.54)	(1.99)
Carhart four-factor α	−0.19	−0.14	−0.23	−0.04	−0.11	0.08	0.37**	0.48*
	(1.10)	(1.02)	(1.63)	(0.20)	(0.60)	(0.48)	(2.25)	(1.95)
HXZ q-factor α	−0.39	−0.32**	0.00	0.39	−0.07	0.05	0.76***	0.83***
	(1.13)	(2.39)	(0.02)	(1.59)	(0.34)	(0.28)	(4.03)	(3.03)
Fama and French five-factor α	−0.54	−0.50***	0.27	−0.27	−0.42	−0.31	0.33*	0.75***
	(1.37)	(4.17)	(1.66)	(1.50)	(1.22)	(1.67)	(1.94)	(3.21)

intensive group are −0.14%, −0.17%, and 0.54%, with t-statistics of 0.64, 1.08, and 4.44, respectively. The alpha on the high-minus-low competition portfolio is as large as 68 basis points (t-statistic = 2.79) per month, which corresponds to an annual premium of almost 8%. In contrast, the corresponding estimates for the R&D-weak group are 0.15%, −0.20%, and 0.04%, with t-statistics of 0.79, 1.58, and 0.33, respectively. The alpha on the high-minus-low competition portfolio is −0.11% and insignificant (t-statistic = 0.49). Moreover, the Carhart four-factor alpha and the Fama and French five-factor alpha on the high-minus-low competition portfolio for the R&D-intensive group are 0.43% and 0.79%, with t-statistics of 1.88 and 3.57, respectively, and these estimates for the R&D-weak group are −0.20% and −0.05%, with t-statistics of 1.34 and 1.67, respectively.

The results in Panel B display a similar pattern. The monthly equal-weighted q-factor alphas on the low, medium, and high competition portfolios for the R&D-intensive group are 0.07%, 0.02%, and 0.77%, with t-statistics of 0.34, 0.11, and 5.70, respectively. The alpha on the high-minus-low competition portfolio is 70 basis points per month (t-statistic = 2.86), which translates to 840 basis points annually. In contrast, the alpha spread is only −0.14% and insignificant (t-statistic = 1.09) for the R&D-weak group. In addition, the Carhart four-factor alpha and the Fama and French five-factor alpha on the high-minus-low competition portfolio for the R&D-intensive group are larger than the corresponding estimates in Panel A: 0.56% and 0.86%, with t-statistics of 2.66 and 4.15, respectively.

Third, whereas the equal-weighted factor-adjusted return spread between competitive and concentrated industries in Hou and Robinson (2006) is 36 basis points per month over the period from 1963 to 2001, the abnormal return spread obtained in the present study is almost twice as large as that figure. Thus, the results in Table 2 strongly support the hypothesis that the competition premium is much more pronounced for firms with aggressive R&D inputs.

Hoberg and Phillips (2010) construct an alternative Herfindahl Index using a sample that includes both public and private firms. As a robustness check, I also perform the double-sorting test using this alternative Herfindahl Index. Tables 3 and 4 show the R&D-return relation and the competition-return relation, respectively. As shown, the return patterns for all the asset pricing models and for both NYSE breakpoints and all-but-micro breakpoints are qualitatively and quantitatively similar to the return patterns in Tables 1 and 2. For example, in Panel B of Table 3, the monthly equal-weighted q-factor alphas on the low, medium, and high R&D-intensity portfolios are 0.00%, 0.45%, and 0.76%, with t-statistics of 0.02, 3.36, and 4.03,

Table 5
Financial constraints subsample studies.

This table reports the monthly raw returns and abnormal returns (α, in percent) on portfolios sorted on product market competition and research and development (R&D) intensity for both financially constrained and financially unconstrained subsamples. Product market competition is measured by the Herfindahl-Hirschman Index (HHI), which is computed based on the market share of each firm in the industry. The detailed definition is provided in Section 3. R&D intensity is defined as R&D expenditure scaled by market equity (RD/ME). Financial constraint is proxied by the *WW* index in Whited and Wu (2006). In Panels A and B, the sample is restricted to financially constrained (i.e., above the median) and financially unconstrained (i.e., below the median) firms, respectively. In each panel, I report value-weighted returns when using NYSE breakpoints, and I report equal-weighted returns when using all-but-micro breakpoints. The sample period is from July 1963 to December 2013. *t*-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	Low competition				High competition			
	$R\&D_L$	$R\&D_M$	$R\&D_H$	H − L	$R\&D_L$	$R\&D_M$	$R\&D_H$	H − L
Panel A: Financially constrained subsample								
NYSE breakpoints and value-weighted returns								
Raw return	0.55*	0.56*	0.94***	0.39	0.46	0.90**	1.32***	0.86***
	(1.88)	(1.97)	(2.62)	(0.95)	(1.29)	(2.32)	(3.18)	(3.62)
Carhart four-factor α	−0.46*	−0.28	−0.05	0.41	−0.53	−0.01	0.22***	0.75***
	(1.91)	(1.05)	(1.12)	(1.13)	(1.31)	(0.09)	(3.10)	(3.29)
HXZ q-factor α	−0.52	−0.22	0.12	0.64*	−0.47**	0.26	0.48**	0.95***
	(1.66)	(0.77)	(1.28)	(1.90)	(2.48)	(1.45)	(2.53)	(4.04)
Fama and French five-factor α	−0.42*	−0.30	0.03	0.45*	−0.39**	0.31**	0.41**	0.80***
	(1.82)	(1.11)	(1.00)	(1.69)	(2.24)	(2.21)	(2.56)	(3.53)
All-but-micro breakpoints and equal-weighted returns								
Raw return	0.72**	0.76**	0.98**	0.26	0.91***	1.08***	1.49***	0.58***
	(1.99)	(2.21)	(2.34)	(1.09)	(2.76)	(3.07)	(3.73)	(2.82)
Carhart four-factor α	−0.06	−0.27	0.19	0.25	−0.04	0.25**	0.50***	0.54***
	(0.30)	(1.22)	(0.51)	(0.60)	(0.37)	(2.32)	(3.40)	(2.79)
HXZ q-factor α	−0.17	−0.41*	0.12	0.29	0.10	0.58***	0.79***	0.69***
	(0.73)	(1.72)	(0.30)	(0.63)	(0.73)	(4.39)	(4.68)	(3.38)
Fama and French five-factor α	−0.29	−0.44*	−0.11	0.18	−0.07	0.36***	0.48***	0.55***
	(1.35)	(1.87)	(0.27)	(0.42)	(0.49)	(2.91)	(2.93)	(2.85)
Panel B: Financially unconstrained subsample								
NYSE breakpoints and value-weighted returns								
Raw return	0.99***	0.77***	0.98***	−0.01	0.93***	1.01**	1.41***	0.48**
	(4.85)	(3.77)	(4.40)	(0.02)	(4.31)	(4.58)	(5.25)	(2.52)
Carhart four-factor α	0.12	−0.04	0.07	−0.05	0.07	0.27***	0.42***	0.35*
	(1.25)	(0.24)	(0.33)	(1.24)	(0.63)	(3.62)	(3.57)	(1.94)
HXZ q-factor α	0.22	−0.30	−0.15	−0.37	0.07	0.30***	0.52***	0.45**
	(1.12)	(1.60)	(0.67)	(1.20)	(0.61)	(3.58)	(4.13)	(2.36)
Fama and French five-factor α	0.16	−0.29	−0.30	−0.46*	0.11	0.29***	0.42***	0.31**
	(1.40)	(1.68)	(1.48)	(1.91)	(0.94)	(3.76)	(3.52)	(1.99)
All-but-micro breakpoints and equal-weighted returns								
Raw return	0.93***	0.88***	0.89***	−0.04	1.14***	1.14***	1.49***	0.35**
	(3.10)	(2.66)	(2.76)	(0.18)	(4.56)	(4.86)	(5.13)	(2.50)
Carhart four-factor α	0.17*	0.04	−0.08	−0.25	0.08	0.16**	0.41***	0.33**
	(1.85)	(0.27)	(0.42)	(1.54)	(0.91)	(2.38)	(3.77)	(2.32)
HXZ q-factor α	0.15	−0.10	−0.12	−0.27	0.11	0.21***	0.54***	0.43***
	(0.97)	(0.62)	(0.51)	(1.08)	(1.03)	(2.73)	(4.47)	(2.92)
Fama and French five-factor α	0.04	−0.17	−0.42**	−0.46*	−0.05	0.06	0.29**	0.34**
	(0.28)	(1.19)	(1.99)	(1.91)	(0.46)	(0.75)	(2.37)	(2.36)

respectively. This translates to an R&D premium of as high as 76 basis points per month. Similarly, in Panel B of Table 4, the monthly equal-weighted q-factor alphas on the low, medium, and high competition portfolios are −0.07%, 0.05%, and 0.76%, with t-statistics of 0.34, 0.28, and 4.03, respectively. The competition premium is as large as 83 basis points per month and statistically significant at the 1% level. Therefore, these results confirm my main findings.

In sum, my results from the conventional double-sorting scheme clearly show a strong positive interaction effect between product market competition and R&D investment on stock returns.

4.2. Tests of alternative mechanisms

In this subsection, I perform subsample studies or use alternative asset pricing models to test alternative mechanisms that could obscure the interpretation of my findings.

First, the effect of financial constraints is explored. Li (2011) demonstrates that the positive R&D-return relation prevails only among financially constrained firms and that a positive financial constraint-return relation exists only among R&D-intensive firms. The author argues that financially constrained firms are more likely to suspend their ongoing R&D projects, which makes the ventures riskier. This argument would provide a reasonable explanation for

Table 6
Innovation ability subsample studies.

This table reports the monthly raw returns and abnormal returns (α, in percent) on portfolios sorted on product market competition and research and development (R&D) intensity for both low- and high-innovation-ability subsamples. Product market competition is measured by the Herfindahl-Hirschman Index (HHI), which is computed based on the market share of each firm in the industry. R&D intensity is defined as R&D expenditure scaled by market equity (RD/ME). Following Cohen, Diether, and Malloy (2013), innovation ability is computed as the average of the coefficients from the regressions of sales on the previous five-year R&D investments. In Panels A and B, the sample is restricted to low-innovation-ability (i.e., below the median) and high-innovation-ability (i.e., above the median) firms, respectively. In each panel, I report value-weighted returns when using NYSE breakpoints, and I report equal-weighted returns when using all-but-micro breakpoints. The sample period is from July 1963 to December 2013. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	Low competition				High competition			
	$R\&D_L$	$R\&D_M$	$R\&D_H$	H − L	$R\&D_L$	$R\&D_M$	$R\&D_H$	H − L
Panel A: Low-innovation-ability subsample								
NYSE breakpoints and value-weighted returns								
Raw return	0.95***	0.88***	0.90***	−0.05	0.84***	0.83***	1.26***	0.42*
	(2.75)	(2.85)	(2.99)	(0.32)	(3.64)	(3.86)	(4.47)	(1.95)
Carhart four-factor α	0.26	−0.13	−0.20	−0.46	0.11	0.14	0.40**	0.29*
	(1.18)	0.56)	(0.61)	(1.06)	(0.62)	(1.23)	(2.37)	(1.74)
HXZ q-factor α	−0.01	−0.30	−0.44	−0.43	0.10	0.15	0.57***	0.47**
	(0.03)	(1.22)	(1.21)	(0.32)	(0.47)	(1.22)	(3.32)	(2.50)
Fama and French five-factor α	0.14	−0.41*	−0.40**	−0.54	0.02	0.11	0.39***	0.37*
	(0.47)	(1.73)	(2.14)	(0.85)	(0.66)	(0.96)	(2.79)	(1.93)
All-but-micro breakpoints and equal-weighted returns								
Raw return	1.29***	1.15***	0.95**	−0.34	1.09***	1.05***	1.63***	0.54**
	(3.47)	(4.21)	(2.48)	(1.29)	(4.43)	(4.76)	(5.42)	(2.36)
Carhart four-factor α	0.22	0.03	−0.32	−0.54	0.20	0.19**	0.57***	0.37**
	(1.15)	(0.15)	(1.15)	(1.28)	(1.23)	(2.04)	(4.05)	(2.45)
HXZ q-factor α	0.37	−0.27	−0.05	−0.42	0.11	0.21*	0.74***	0.63***
	(0.92)	(1.31)	(0.18)	(0.67)	(0.59)	(1.94)	(5.08)	(2.73)
Fama and French five-factor α	0.10	−0.17	−0.67**	−0.77*	0.15	0.14	0.50***	0.35**
	(1.08)	(0.82)	(2.28)	(1.93)	(0.89)	(1.44)	(3.35)	(2.41)
Panel B: High-innovation-ability subsample								
NYSE breakpoints and value-weighted returns								
Raw return	1.32***	0.66**	0.99***	−0.33	1.03***	1.08***	1.57***	0.54**
	(3.17)	(2.40)	(2.74)	(0.87)	(3.90)	(5.13)	(6.15)	(2.53)
Carhart four-factorα	0.32	−0.37	−0.16	−0.48	0.14	0.41***	0.58***	0.44**
	(0.92)	(1.75)	(0.54)	(1.11)	(0.67)	(3.48)	(3.78)	(2.46)
HXZ q-factor α	0.17	−0.61	−0.20	−0.37	0.03	0.40***	0.55***	0.52***
	(0.43)	(0.74)	(0.65)	(0.95)	(0.11)	(3.08)	(3.37)	(2.69)
Fama and French five-factor α	0.24	−0.50**	−0.68**	−0.92**	0.07	0.39***	0.48***	0.41**
	(0.65)	(2.38)	(2.24)	(2.08)	(0.79)	(3.23)	(3.08)	(2.53)
All-but-micro breakpoints and equal-weighted returns								
Raw return	1.24***	0.65**	0.77***	−0.47	0.84***	1.01***	1.47***	0.63***
	(4.07)	(2.29)	(3.00)	(0.11)	(3.55)	(4.47)	(5.12)	(2.85)
Carhart four-factor α	0.27	−0.40**	−0.15	−0.42	−0.09	0.13	0.41***	0.50**
	(0.99)	(2.07)	(0.45)	(0.78)	(0.60)	(1.28)	(2.86)	(2.50)
HXZ q-factor α	0.04	−0.39*	−0.31	−0.35	−0.10	0.18*	0.55***	0.65***
	(0.12)	(1.90)	(0.80)	(0.32)	(0.62)	(1.69)	(3.77)	(3.13)
Fama and French five-factor α	0.00	−0.60***	−0.52	−0.52	−0.17	0.03	0.37**	0.54***
	(0.00)	(3.02)	(1.45)	(0.79)	(1.12)	(0.31)	(2.44)	(2.58)

my results if firms in competitive industries were more likely to be financially constrained than firms in concentrated industries. To rule out this possibility, I test my findings while controlling for financial constraints. The full sample is divided into financially constrained and financially unconstrained subsamples on the basis of the median value of the distribution of the *WW* index from Whited and Wu (2006).[11] Table 5 reports the monthly raw returns and abnormal returns on the double-sorted portfolios. Panels A and B show the R&D-return relation in competitive and concentrated industries for financially constrained and financially unconstrained subsamples, respectively.

As shown in both panels, controlling for financial constraints does not weaken my main findings. The return pattern in Table 1 prevails in both financially constrained and financially unconstrained subsamples (i.e., the positive and significant return and abnormal return on the high-minus-low R&D-intensity portfolio exists only in competitive industries). For instance, when I use NYSE breakpoints to examine the financially unconstrained subsample in Panel B, the monthly value-weighted q-factor alpha on the high-minus-low R&D-intensity portfolio in competitive industries is 0.45% and significant (t-statistic = 2.36) and the

[11] The *SA* index from Hadlock and Pierce (2010) is also used to measure financial constraints and qualitatively similar results are obtained. These results are available in the Internet Appendix.

alpha is −0.37% and insignificant (t-statistic=1.20) in concentrated industries. When analyzed using all-but-micro breakpoints, the monthly equal-weighted q-factor alphas on the high-minus-low R&D-intensity portfolio in competitive and concentrated industries are 0.43% (t-statistic=2.92) and −0.27% (t-statistic=1.08), respectively. Qualitatively similar results are obtained for the Carhart (1997) four-factor model and the Fama and French (2015) five-factor model, as well as for the financially constrained subsample. Thus, the test results suggest that financial constraints cannot explain the important role competition plays on the R&D-return relation.

Moreover, consistent with Li (2011), the positive R&D-return relation in competitive industries is more pronounced in the presence of financial constraints. In all cases, the return on the high-minus-low R&D-intensity portfolio is larger for the financially constrained subsample than that for the financially unconstrained subsample. For instance, when analyzed using NYSE breakpoints, the monthly value-weighted q-factor alpha spread across R&D-intensity portfolios in competitive industries is 0.95% (t-statistic=4.04) for the financially constrained subsample and 0.45% (t-statistic=2.36) for the financially unconstrained subsample. The difference is as large as 50 basis points per month. Similarly, when analyzed using all-but-micro breakpoints, the monthly equal-weighted q-factor alpha spread across R&D-intensity portfolios in competitive industries is 0.69% (t-statistic=3.38) for the financially constrained subsample and 0.43% (t-statistic=2.92) for the financially unconstrained subsample. The difference is 26 basis points per month.

In addition, the positive R&D-return relation does not exist in concentrated industries for the financially constrained subsample. This observation indicates that financial constraints do not appear to affect the R&D-return relation once competition is controlled for. The results using subsamples constructed on the basis of the *SA* index in Hadlock and Pierce (2010) deliver identical insights.

The next point of examination is the effect of innovation ability, as proposed by Cohen, Diether, and Malloy (2013), who provide evidence that R&D intensity predicts future returns only when firms have a high ability to translate the outcome of innovation projects into real sales growth. These authors demonstrate a significantly positive adjusted return associated with *GOODR&D* (i.e., high R&D intensity and high innovation ability) firms. If R&D-intensive firms in competitive industries also have high abilities to translate R&D projects into sales growth, then innovation ability could justify my findings.

Following Cohen, Diether, and Malloy (2013), innovation ability is computed as the average of the coefficients from the regressions of sales on R&D investments over the previous five-year period.[12] Then, I create the low- (i.e., below the median) and high- (i.e., above the median) innovation-ability subsamples and estimate the raw returns and abnormal returns on the double-sorted portfolios for each subsample. Panels A and B in Table 6 show the R&D-return relation in competitive and concentrated industries for two different innovation-ability subsamples, respectively.

Three conclusions can be reached from Table 6. First, my main findings still hold in both low- and high-innovation-ability subsamples. In other words, the positive and significant return on the high-minus-low R&D-intensity portfolio in competitive industries is identified in both subsamples. For example, when all-but-micro breakpoints are used to examine the low-innovation-ability subsample in Panel A, the monthly equal-weighted q-factor alpha on the high-minus-low R&D-intensity portfolio in competitive industries is 0.63% and significant (t-statistic=2.73) and the corresponding alpha is −0.42% and insignificant (t-statistic=0.67) in concentrated industries. Similarly, in Panel A, when analyzed using NYSE breakpoints, the value-weighted q-factor alphas on the high-minus-low R&D-intensity portfolio in competitive and concentrated industries are 0.47% (t-statistic=2.50) and −0.43% (t-statistic=0.32), respectively. Thus, these findings suggest that innovation ability cannot be the reason that competition drives a significant portion of the R&D-return relation.

Second, consistent with Cohen, Diether, and Malloy (2013), the positive R&D-return relation is stronger for the high-innovation-ability subsample. For example, when analyzed using NYSE breakpoints, the monthly value-weighted Carhart four-factor alpha on the high-minus-low R&D-intensity portfolio in competitive industries is 0.29% (t-statistic=1.74) for the low-innovation-ability subsample and 0.44% (t-statistic=2.46) for the high-innovation-ability subsample. The alpha difference is 15 basis points per month. Moreover, when analyzed using all-but-micro breakpoints, the monthly equal-weighted Carhart four-factor alphas on the high-minus-low R&D-intensity portfolio in competitive industries are 0.37% (t-statistic=2.45) for the low-innovation-ability subsample and 0.50% (t-statistic=2.50) for the high-innovation-ability subsample, respectively. This corresponds to an alpha difference of 13 basis points per month. Although the alpha difference is smaller for the Hou, Xue, and Zhang (2015) q-factor model and the Fama and French (2015) five-factor model, this difference is consistently positive.

Finally, the high R&D-intensity portfolio in the high-innovation-ability subsample is not associated with a positive and significant return when firms are also in concentrated industries. This finding indicates that innovation ability does not seem to affect the R&D-return relation once competition is controlled for. To summarize, the test results regarding financial constraints and innovation ability reveal that competition is an independent driver of the R&D premium.

The abnormal returns on the double-sorted portfolios are also estimated by augmenting the asset pricing models with additional factors proposed by other researchers. This test serves two purposes. First, it constitutes an additional robustness check for my results. Second, the abnormal returns identified in the tests could be driven by omitted firm characteristics that are correlated with R&D investment or product market competition, but that are not captured by the asset pricing models used in this study. Thus, additional

[12] The details of the computation can be found in Cohen, Diether, and Malloy (2013).

factors can provide information that helps identify the potential mechanisms driving the return patterns. The portfolio returns when the liquidity factor of Pastor and Stambaugh (2003) is included in the asset pricing model are available in the Internet Appendix. As shown, adding the liquidity factor does not weaken my findings.

5. Conclusion

This paper tackles two asset pricing puzzles by testing the joint effect of product market competition and R&D investment on stock returns, and it provides new perspectives on the positive competition-return and R&D-return relations that have drawn a fair amount of attention from economists. In competitive industries, firms frequently must enter innovation races with many rivals for new products or technologies. The potential future cash flows associated with R&D projects are more likely to be extinguished in competitive industries because rivals could win the innovation race. Therefore, competition raises the exercise thresholds for R&D investment options and magnifies R&D-intensive firm's exposure to the systematic risk.

These insights are confirmed by the empirical findings that the positive R&D-return relation exists only in competitive industries and that the competition-return relation exists only among R&D-intensive firms. Further tests show that the role of competition cannot be explained by financial constraints or innovation ability, which have been identified as factors that affect the R&D-return relation.

In close, this study suggests that competition has a significant impact on R&D-intensive firms' risk and return profiles and thus independently drives a significant portion of the R&D premium. Moreover, this paper proposes a potential mechanism through which market structure affects a firm's risk dynamics, thereby providing a risk-based explanation for the heretofore puzzling competition-return relation.

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