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The Innovation Premium

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Disciplines
Finance and Financial Management

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Firms that engage in innovative product development, as measured by the fraction of their investment that goes to Research and Development (R&D) activities, earn higher risk-adjusted equity returns. A portfolio that goes long the most innovative and shorts the least innovative firms earns a risk-adjusted return in excess of 7% per annum. R&D-intensive firms also tend to charge higher price markups. Combining insights from industrial organization with a production-based asset pricing framework, I propose a model in which heterogeneous firms produce vertically differentiated goods and market them to heterogeneous consumers. Firms are subject to aggregate demand and supply shocks, which are both priced by investors, and thus the return premium of innovative firms is explained by their differential exposures to these shocks. In addition to explaining this return spread, the model makes predictions on firm investments, future profit markups, and firm size that are consistent with the data.

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1 Introduction

Research and development (R&D) activities are widely cited as a key driver of both firm-specific technological progress and aggregate economic growth. R&D is becoming an increasingly important investment activity for private corporations in particular, as firms shift from dependence on physical capital to intangible and knowledge capital (Congressional Budget Office (2005)). This shift is perhaps best illustrated by the change in investment composition: Figure 1 plots the cumulative growth in both physical capital investment and R&D investment over time. Growth in R&D investment has clearly and significantly outpaced growth in physical investment, a trend that holds across industries and firm size. For example, manufacturing firms alone now spend over $100 billion in R&D annually, more than the (inflation-adjusted) R&D spending of the entire public and private sectors 40 years ago. Both within industries and across industries, there is significant variation in how much investment firms attribute to R&D.

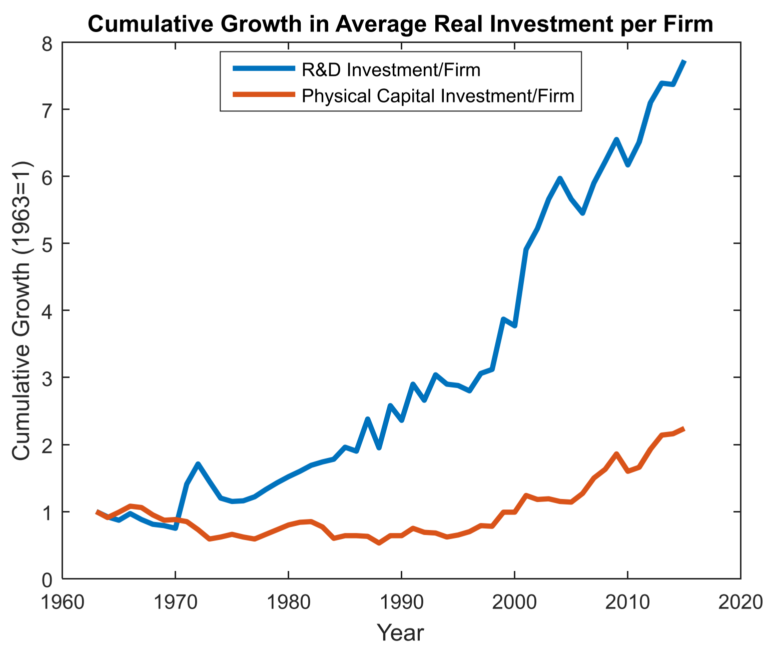

Figure 1: Cumulative Growth in Average Investment per Firm

This paper shows that firms that devote more of their investment to R&D activities earn higher risk-adjusted equity returns. It also rationalizes this finding with a model featuring heterogeneous firms and heterogeneous consumers which generates a risk premium for R&D through a novel product market channel. In examining returns to R&D investments, this paper compares those returns to returns on the most significant other form of investment: investments in physical capital. To this end, the measure of a firm's R&D intensity employed in this analysis will be the fraction of total investment expense in a given year allocated to R&D. This metric is clearly an important determinant for firm equity returns: Figure 2 plots the cumulative annual stock returns for firms with low levels of R&D/total investment, firms with high levels of R&D/total investment, and the aggregate value-weighted market. Firms with a higher ratio of R&D/investment earn significantly higher cumulative returns.

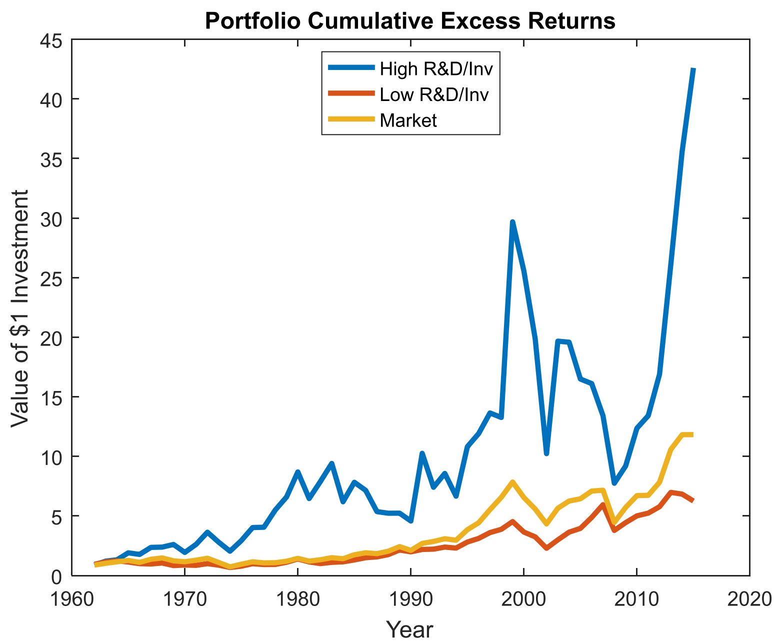

Figure 2: Portfolio Cumulative Excess Returns to $1 invested in January 1962

Are these returns compensation for risk? This paper shows that standard risk factors do not explain these returns. Relative to the most common models for expected returns in the literature, firms that allocate most of their investment towards R&D continue to earn higher returns than predicted. Specifically, these firms generate an annual return over 7% higher than that predicted by the Fama-French 3-factor model and an annual return that is 10% above the expected return predicted by the Fama-French 5-factor model. In any rational asset pricing framework, these excess returns must be attributable to some risk factor not spanned by these existing models. Moreover, this paper finds that the risk factor captured by the R&D/investment ratio is important not only to understand the returns of R&D-intensive firms, but also to understand the entire cross-section of stock returns. In Fama-MacBeth tests, the risk factor embedded in these high R&D-intensity firms has a positive and significant price of risk for the entire cross-section.

To understand the risks of these high-R&D firms, it is important to first understand why firms would want to devote a significant fraction of their investment towards intangible capital. While expenditures such as research salaries, blueprint and patent creation, and technology development may not directly enable a firm to produce a higher quantity of products, they often enable it to produce products of a higher quality. Indeed, for many firms, significant R&D expenses are necessary to maintain a competitive market position. This is reflected in the empirical finding documented in the paper that these high-R&D firms also charge significantly higher price markups over cost for their products. Furthermore, the returns on these high-R&D firms can be linked to consumers' expenditures on luxury goods, which are also typically high-markup products (as studied by Ait-Sahalia et al. (2004)).

The final contribution of the paper is then to integrate this key insight that high R&D is connected with higher product quality and price markup into a production-based asset pricing model. The model features heterogeneous firms that create products of different quality levels, with firms that produce higher quality products requiring a greater amount of R&D per unit of physical capital used for production. These firms offer price and quality combinations to heterogeneous consumers, who choose the product that maximizes their utility every period. The economy is subject to total factor productivity shocks which affect the productivity of physical capital and demand shocks which affect the preferences of consumers. The model parsimoniously captures the empirical observation that higher-R&D firms are more exposed to demand fluctuations. This higher exposure explains their higher returns. The model also matches the size and markup dynamics in the data.

This paper is related to several strands of the existing literature. First, there have been several empirical asset pricing studies that focus on how some form of intangible investment affects future equity returns. Perhaps the most noted of these is the 2001 paper by Chan, Lakonishok, and Sougiannis showing that a firm's ratio of R&D expenditures to market equity is related to its future abnormal equity return. Li (2011) studies the interaction between measures of R&D expenditures and financial constraints. Several other papers have studied variants on the R&D anomaly by focusing on firms that have been successful in past R&D (Cohen et al. (2013)) and innovative efficiency (Hirshleifer et al. (2013). These papers have found interesting results in focusing on segments of high R&D-intensity firms that seem to drive the broader set of results. This paper, however, will take the view that another measure of R&D intensity is more informative altogether. In particular, the metric in this paper is important for understanding the returns of larger and more economically important firms and helps to price the entire cross-section of stock returns, two signficiant deviations from the existing literature. Finally, a recent paper by Kogan et al. (2016) has argued that patent creation is important for aggregate economic growth, which will be outside the scope of the analysis considered in this paper.

Second, there have been several structural asset pricing papers which have considered the relationship between equity returns and intangible investment or capital. Lin (2012) is the closest to this analysis; he proposes a model in which intangible capital reduces adjustment costs to physical capital and so drives excess returns of high R&D/Investment firms. Other similar papers include Corhay, Kung, and Schmid (2015), who propose a model linking markups, competition, and stock returns, and Eisfeldt and Papanikolaou (2013), who link organizational capital and expected stock returns. This paper will differ from all of those studies by introducing a different and largely novel mechanism of product market competition to drive the cross-sectional implications. It differs from the first two by also focusing on the cross-section of expected risk-adjusted returns. The R&D/investment measure considered in this paper is also not closely related to the organizational capital measure of Eisfeldt and Papanikolau (2015). Lastly, several papers have focused on the idea that R&D expenditures by firms can drive endogenous growth in the aggregate economy, such as Kung and Schmid (2015) and Ai, Croce, and Li (2012), but this paper will focus on a different channel and will have significantly different cross-sectional implications.

The rest of the paper proceeds as follows. Section 2 describes the data used in the paper, the empirical asset pricing results of the paper, and the empirical motivation for the model. Next, section 3 introduces the model and discusses each component. Section 4 presents the calibration and results of the model. Finally, section 5 concludes.

2 Data and Empirical Results

2.1 Data Sources and Definitions

The data from this project come primarily from the CRSP/Compustat Merged dataset on WRDS. Firm-level accounting data come from Compustat and include balance sheet items (stocks of capital, assets, and capital structure measures) and income and cash flow statement items (revenue, cost of goods sold, R&D expenses, and capital expenditures). Due to the often significant seasonality of many of these series, such as investment expenditures and revenues, observations are collected on an annual basis. The SIC codes 0-999 (agriculture, fishing, hunting), 4900-4999 (utilities), 6000-6999 (financials), 8888 (foreign governments), and 9000-9999 (international/non-operating) were also eliminated for most of the analyses in this paper. Finally, companies that did not report R&D expenditures (about half of the firm-year observations in the sample) were eliminated. The asset pricing results for these firms were quantitatively similar to those for firms that reported zero values of R&D expenditures.

The key ratio of interest for much of this paper will be the fraction of total investment spent on R&D expenses. For this purpose, total investment will be defined as the sum of R&D expenses and capital expenditures. The reporting standard for firms are set by the Generally Accepted Accounting Principles (GAAP), which defines R&D expenses as part of the "planned search or critical investigation aimed at discovery of new knowledge...in developing a new product or service or a new process or technique" or part of the "translation of research findings into a plan or design for a new product or process." R&D is typically differentiated into product development (developing new products or services) and process development (developing new techniques or methods to produce existing offerings) and includes expenses such as research wages, patent development, and software development, with wages making up up to 50% of total R&D in some industries (Hall and Lerner (2010)). Capital expenditures, meanwhile, include all costs in purchasing and making ready for use property, plant, and equipment additions. These typically include long-lived tangible assets such as land, buildings, machinery, equipment, fixtures, and others.

Some have also suggested that selling, general, and administrative (SG&A) expenses and R&D expenses are cross-reported by firms, with some firms reporting as an R&D expense what other firms would report as an SG&A expense (see e.g. Peters and Taylor (2016)). To take this consideration into account, the empirical asset pricing results are also computed using the ratio of the sum of R&D and SG&A expenses to the sum of R&D expenses, SG&A expenses, and capital expenditures. The results are quantitatively similar. Of the firm-year observations for which R&D expenditures are reported, 17% of those observations have reported values of 0 R&D expenses. Of the remaining 83%, the distribution is fairly uniform, as illustrated in Figure 5.

Another definition employed by the paper is a metric of markups, which is used for one result in Section 2.4. While there are many measures of aggregate markups that have been used in similar papers and in the industrial organization literature, in order to get a firm-specific measure of price markups, this paper simply uses the ratio of Revenues to Cost of Goods Sold (COGS) minus 1. This gives the percentage markup over the cost of goods that firms are charging. Others have suggested including other expenses in COGS, such as SG&A expenses, and these changes do not impact the results in Section 2.4. Summary statistics of firms by their level of R&D/Investment are available in Table 4. Higher R&D/Investment firms tend to be smaller, less levered, and have fewer tangible assets. They also tend to charge higher prices relative to product costs and earn higher revenues relative to physical capital (but not total assets, perhaps a reflection of other intangible capital that is included in their asset base).

The Compustat data was then merged with equity returns from CRSP based on the permanent "permco" link between the two. Monthly CRSP returns were collected and are the basis for all of the asset pricing results to follow. From French's website, the monthly excess returns of the market, HML, SMB, RMW, and CMA factors were obtained. Finally, the data series on luxury good sales used by Ait-Sahalia et al. (2004) was also obtained from Yogo's website.

2.2 Alpha Sorts

This section is devoted to the analysis of the question of whether the higher returns associated with more R&D-intensive firms are compensation for a recognized risk factor. To analyze this, this paper starts by analyzing the returns of R&D-intensive firms relative to the benchmark model for excess return used in the vast majority of the empirical asset pricing literature, the Fama-French 3-factor model. This model says that excess returns on a given security should be given by equation (1):

$$r_{it}^{e} = \alpha_i + \beta_{it}^{rmrf} RMRF_t + \beta_{it}^{hml} HML_t + \beta_{it}^{smb} SMB_t + \epsilon_{it} \tag{1}$$

where r_{it}^{e} represents the return on stock i at time t in excess of the risk free rate. If the model holds, then the average α over the cross-section of stocks (or for any portfolio of stocks) should be zero, and the only factors affecting excess returns should be exposures to the excess return on the value-weighted market factor $RMRF$, the high minus low book equity to market equity factor (value minus growth) HML, and the small minus big market cap factor SMB (Fama and French (1992)).

To test this model, firms are sorted into eleven portfolios based on their R&D/Investment ratio. One portfolio contains the firms which report 0 R&D values, while the remaining ten represent the firms which fall into each decile of the R&D/Investment distribution. As Figure 5 illustrates, the approximately uniform distribution of the R&D/Investment measure means that the unit support of R&D/Investment will be fairly evenly divided among these deciles. The portfolios are rebalanced every year with new accounting data, which means that firms will move across deciles as their level of R&D/Investment changes every year. Table 5 gives the transition matrix from one year to the next for the R&D/Investment deciles. The persistence of this measure is significantly higher than those for commonly cited asset pricing anomalies, such as the book-to-market, profitability, investment, and momentum factors, as evidenced by Opp and van Binsbergen (2016).

The value-weighted returns of the firms in the portfolio form the time series of returns for each portfolio. To test the Fama-French 3-factor model, the time series of returns for each portfolio is regressed on the time series of returns for the market excess return and the HML and SMB factors.

If the Fama-French 3-factor model correctly prices these assets, then the average excess returns of these portfolio should be explained by their exposures to these three factors and there should be no significant intercept term in the regression results. Table 1 presents the results for the intercept and coefficient terms for each portfolio. The columns of the table represent the various portfolios, from 0 (the portfolio of firms that report R&D values of 0) to the deciles of R&D/Investment (1-10), to "10-1", which represents the zero-cost portfolio of buying portfolio 10 and short-selling portfolio 1 (similar results hold if one short-sells portfolio 0). Examining the first two rows, which report the intercept (α) regression results and their Newey-West t-statistics, one sees that the pricing errors increase in the R&D/Investment decile, becoming positive and significant for deciles 6, 7, 8, 10 and the long-short 10-1 portfolio. This implies that if one buys portfolio 10 and short-sells portfolio 1, he earns a monthly return of 58bps (7.2% annualized) in excess of what the Fama-French 3-factor model would predict based on this portfolio's exposures to the three Fama-French factors. This α is statistically significant at the 5% level and thus indicates a violation of the model.

	R&D/Investment Decile											
	0	1	2	3	4	5	6	7	8	9	10	10-1
α	-0.026	-0.057	0.028	0.065	-0.026	0.094	0.219	0.301	0.470	0.099	0.523	0.580
	(-0.36)	(-0.61)	(0.32)	(0.75)	(-0.30)	(1.01)	(2.33)	(2.63)	(3.34)	(0.61)	(2.90)	(2.78)
$RMRF$	0.909	0.890	1.064	1.046	1.037	1.015	0.950	1.023	1.036	1.025	1.095	0.206
HML	0.130	0.155	0.153	-0.036	-0.139	-0.299	-0.354	-0.450	-0.602	-0.830	-0.794	-0.950
SMB	-0.142	-0.226	-0.158	0.078	0.004	0.035	0.022	0.137	0.238	0.592	0.848	1.074

Table 1: R&D/Investment Decile Portfolio Regressions on Fama-French 3 Factors. First row gives Fama-French 3-Factor alphas, with Newey-West t-statistics below. Bottom 3 rows give portfolio betas with respect to Fama-French 3 factors.

The bottom three rows also reveal information about the risks of the firms in these portfolios. Exposure to the aggregate market risk factor, RMRF, is roughly constant across deciles, indicating that there are no significant differences in the exposures of the high-R&D versus the low-R&D firms to the risks spanned by the aggregate stock market. This is an interesting result in itself as it suggests that the connection between R&D-intensive firms and high-beta firms is not as close as some have suggested, which may be due to the focus on just the composition of investment (rather than the composition and amount of investment which some measures combine). There are, however, significant differences in the exposures of these firms to HML and SMB. High R&D/Investment firms tend to load far more negatively on HML than do low R&D/Investment firms. This pattern indicates that these firms have lower ratios of book equity to market equity and are more growth firms than value firms, consistent with what one might expect. Similarly, high R&D/Investment firms load more positively on SMB than do low R&D/Investment firms, indicating that these firms tend to be smaller. Still, after accounting for these exposures (which have somewhat offsetting effects due to their opposite signs), the Fama-French 3-factor model fails to fully explain the higher returns of the high R&D/Investment firms.

In response to the documented failures of the Fama-French 3-factor model to explain certain anomalies related to investment and profitability (see e.g. Hou et al. (2015) and Novy-Marx (2013)), Fama and French updated their model to include two additional factors designed to capture the variation in expected returns associated with firms' investment policies and profitability. The updated model is expressed in equation (2):

$$r_{it}^{e} = \alpha_i + \beta_{it}^{rmrf} RMRF_t + \beta_{it}^{hml} HML_t + \beta_{it}^{smb} SMB_t + \beta_{it}^{rmw} RMW_t + \beta_{it}^{cma} CMA_t + \epsilon_{it} \qquad (2)$$

where the first four terms on the right hand side are identical to the previous model and the excess return now includes compensation for the return's exposure to RMW, which represents robust operating profitability minus weak and CMA, which represents conservative investment minus aggressive. Note that operating profitability is computed as $\frac{Revenues - COGS - Interest - SG\&A}{Book\ Equity}$ and so does not explicitly include either R&D expenses or capital expenditures. Similarly, Fama and French define investment as the growth of total assets in the previous year divided by the amount of assets two years past, so neither measure is mechanically linked to the R&D/Investment measure in this paper (Fama and French (2015)).

Given that these revisions explicitly seek to address investment-based anomalies, it is natural to ask whether the R&D/Investment factor which targets the composition of investment can still be used to generate portfolios which earn abnormal returns under the Fama-French 5-factor model. One can perform the same test as before: run a time series regression of the value-weighted returns of each R&D/Investment portfolio on the five Fama-French factors and report the intercept and coefficient values for each portfolio, checking to see whether the portfolios generate positive intercepts. Table 2 gives those results.

Beginning again with the regression intercepts, an even more striking pattern is apparent. Not only are the α values still increasing in the R&D/Investment deciles, but the magnitudes are now significantly higher. Whereas the long high R&D/Investment and short low R&D/Investment portfolio earned risk-adjusted monthly excess returns of 58bps per month under the Fama-French 3-factor, it now earns risk-adjusted excess returns of 82bps per month, or over 10% per year, relative to the Fama-French 5-factor model. One can see why this is the case by examining the factor exposures of this portfolio. The first three coefficients follow similar patterns to their counterparts in the Fama-French 3-factor results. Namely, exposures do the market do not seem to have a significant pattern as R&D/Investment varies but high R&D/Investment firms seem to be more growth firms (negatively exposed to HML) and smaller firms (positively exposed to SMB).

What is different is that these firms are also fairly negatively exposed to the profitability factor, RMW. This result is somewhat consistent with the observation that these firms also tend to have lower Revenue/Asset ratios and lower Asset/Book Equity ratios. Interestingly, the high-R&D/Investment firms and low R&D/Investment firms have very similar exposures to the investment factor. This latter observation suggests that the decomposition between the amount of investment and the composition of investment is an important one. Combined, the exposures to RMW and CMA lower the benchmark for the returns of these high R&D/Investment portfolios under the Fama-French 5-factor model and thus lead to the more significant intercept term.

Tables 21-23 demonstrate that this measure is also robust to other firm-level characteristics. Higher R&D/Investment is positively associated with higher risk-adjusted equity returns after controlling for both gross and net profitability. Within profitability quintiles, firms which do more R&D relative to total investment earn significantly higher Fama-French 3-factor and 5-factor alphas. Similarly, double-sorting first by the amount of investment (relative to total assets) that a firm spends and then by R&D/Investment still produces increasing alphas in the R&D/Investment ratio. This effect is present for all but the firms which invest the least (those in the bottom 20%

	R&D/Investment Deciles											
	0	1	2	3	4	5	6	7	8	9	10	10-1
α	-0.077	-0.054	-0.015	0.085	0.023	0.206	0.240	0.361	0.769	0.325	0.768	0.821
	(-1.01)	(-0.53)	(-0.16)	(0.90)	(0.27)	(2.17)	(2.35)	(3.06)	(5.39)	(2.00)	(4.32)	(3.18)
$RMRF$	0.929	0.900	1.076	1.035	1.028	0.997	0.946	1.005	0.959	0.993	1.070	0.169
HML	0.066	0.091	0.106	0.003	-0.076	-0.287	-0.403	-0.423	-0.410	-0.875	-0.860	-0.951
SMB	-0.130	-0.254	-0.136	0.077	-0.007	-0.035	0.001	0.093	0.106	0.406	0.632	0.887
RMW	0.044	-0.109	0.103	0.010	-0.075	-0.252	-0.056	-0.179	-0.523	-0.706	-0.868	-0.758
CMA	0.152	0.146	0.107	-0.075	-0.125	-0.050	0.092	-0.091	-0.476	0.017	0.095	-0.050

Table 2: R&D/Investment Decile Portfolio Regressions on Fama-French 5 Factors
First row gives Fama-French 5-Factor alphas, with Newey-West t-statistics below. Bottom 5 rows give portfolio betas with respect to Fama-French 5 factors.

of the Investment/Assets ratio.) These results are also robust to other factor-based models for equity returns. Table 24 demonstrates that this effect is amplified when the Quality-minus-Junk factor proposed by Asness et al. (2013) is included as a risk factor. Similarly, Table 25 presents the robustness of these results to the inclusion of a momentum factor.

There are several important differences between these results and those of earlier papers. First, portfolio returns are value-weighted rather than the equal-weighted returns found in the literature. Value-weighting these returns is important for several reasons. First, value-weighting portfolio returns both prevents big price changes to small market cap firms from having an outsized impact on portfolio returns. Thus value-weighting focuses on the larger and more central firms and is thus more meaningful from an economic standpoint. Table 15 shows this explicitly by double-sorting firms into groups based on assets and then R&D measures. For the R&D/Investment metric employed in this paper, there is a significant return differential attributable to R&D-intensive firms across all size quintiles. In comparison, for the R&D/Market Equity measure, the effect is only significant at a 5% level or stronger for the smallest quintile of firms, whose median asset values are 0.25% of those of firms in the highest quintile. This pattern is similar for most other existing R&D measures in the literature.

Second, value-weighting is more in keeping with the asset allocation of one who would hold this portfolio. Equal-weighting requires constant rebalancing of a portfolio and very high associated transactions costs. It is difficult to interpret the returns from such a portfolio as an asset pricing anomaly if the costs of exploiting the strategy outweigh the potential benefits. Thus it is important to value-weight the returns within a portfolio. It is even more important when one considers that the significant asset pricing results that one obtains using equal-weighted portfolio returns with existing asset pricing measures disappear under value-weighting of portfolio returns, as shown in Table 6. Thus, the equal-weighted results arbitrarily overemphasize the importance of small market cap firms and may not truly represent an anomaly. By showing that the results in this paper hold for value-weighted (as well as equal-weighted in Table 7) these concerns are eliminated.

Another important difference the measures of R&D intensity are fairly different. Tables 16-20 report the similarities between the measure introduced in this paper and five other common measures: R&D/Market Equity, R&D/Sales, R&D Capital/Market Equity, R&D/R&D Capital, and SG&A Capital/Assets. The percentage of firms which fall in the same decile when sorted by the measure in this paper as when sorted by these measures is fairly low. This is also evidenced by the fact that the measures themselves are not highly correlated: the highest Pearson or rank correlation between the measure in this paper and any of the existing measures is 0.4. These low correlations reflect an important economic insight captured by the R&D/Investment measure: its focus on the composition of investment. While other measures combine the composition of investment and the amount of investment, the focus on what type of investment a firm is doing, rather than how much it is doing, is an important differentiating factor of this measure. Finally, this measure is the first R&D-based measure to be significantly priced in the full cross-section. This is important as it means that the empirical asset pricing results in this paper are important for understanding the entire cross-section of equity returns.

The Fama-French 3-factor results and 5-factor results clearly indicate that high R&D/Investment portfolios earn significant positive risk-adjusted returns. These firms tend to be smaller, more growth firms, and less profitable by the Fama-French metric but to load similarly on the aggregate market factor and the investment factor as their low R&D/Investment counterparts. Despite these differential loadings, the higher returns of the high R&D/Investment portfolios are not rationalizable by any of the Fama-French factors.

2.3 Fama-MacBeth Results

In any rational asset pricing model, these higher returns must be attributable to some additional source of risk faced by these high R&D/Investment firms and affecting investors' discount rates. A natural follow-up question would then be to ask whether the risk encapsulated in these high R&D/Investment firms is important only for them or for a broader number of firms. This risk is captured by the return of the portfolio going long high R&D/Investment firms and short low R&D/Investment firms, so, to answer this question, this section presents the cross-sectional asset pricing results using this "10-1" portfolio as a factor.

A Fama-Macbeth procedure tests whether this innovation risk factor measure is priced for a larger cross-section of assets. For this analysis, both industry portfolios and the entire dataset of monthly stock returns (not just those of stocks who report R&D values). For the industry portfolio results, the largest cross-section of industries categorized by Fama and French is used for the longest timespan for which all data is available. This results in 49 industries over a period of 559 months. The Fama-Macbeth procedure is computed as follows. First, for each industry/stock at each point in time, rolling-window betas with respect to the High R&D/Investment minus Low R&D/Investment (henceforth referred to as the innovation factor or R&D) and either the Fama-French 3-factor model or the Fama-French 5-factor model. To account for possible covariances between the factors, these betas are estimated simultaneously in two groups: one group with the innovation factor and the Fama-French 3 factors and one group with the innovation factor and the Fama-French 5 factors, given by equations (1) and (2), respectively. After that, at each point in time, a cross-sectional regression of excess returns on betas is computed (again, separate regressions for the 3 factors and R&D from the 5 factors and R&D), and the prices of risk extracted as the λ values in specifications (3) and (4):

$$r_{it}^{e} = \alpha_i + \beta_{it}^{rmrf}\lambda_t^{rmrf} + \beta_{it}^{hml}\lambda_t^{hml} + \beta_{it}^{smb}\lambda_t^{smb} + \beta_{it}^{R\&D}\lambda_t^{R\&D} + \epsilon_{it} \tag{3}$$

$$r_{it}^{e} = \alpha_i + \beta_{it}^{rmrf}\lambda_t^{rmrf} + \beta_{it}^{hml}\lambda_t^{hml} + \beta_{it}^{smb}\lambda_t^{smb} + \beta_{it}^{rmw}\lambda_t^{rmw} + \beta_{it}^{cma}\lambda_t^{cma} + \beta_{it}^{R\&D}\lambda_t^{R\&D} + \epsilon_{it} \tag{4}$$

The choice of test assets (whether industries or individual stocks) represents a trade-off between accuracy of beta estimation and use of a larger cross-section. While the use of portfolios mitigates the errors-in-variables problem associated with estimating time-varying betas for individual stocks and using those estimated betas in a second-stage estimation, the construction and number of the portfolios need to be carefully considered. Industry portfolios are utilized here so that the potential issue of sorting portfolios by characteristics is avoided. Moreover, the broadest set of industries reported is used to obtain as large a cross-section (and hence as powerful a test as possible.) The procedure is also replicated with individual stocks and the results are displayed in Table 9 in the appendix.

Table 3 presents the Fama-Macbeth results for the Fama-French 3-factors and the innovation factor, using the 49 industry portfolios as defined on French's website. Both equally-weighted and value-weighted portfolio returns are considered (with the factor weighting matching the return weighting); the results are robust to choice of portfolio and factor weighting. Across the specifications, both the market factor and the innovation factor both have positive and significant coefficients. Thus, exposure to the market and innovation risk factors are associated with significantly higher expected returns. In particular, an increase by one in market beta is associated with an increased monthly industry return of 42-59 bps, and an increase by one in innovation beta is associated with an increased monthly industry return of 86-89 bps. Moreover, SMB is not significant in either specification and HML is only significant in one of the specifications. Thus, these results suggest that both innovation risk and market risk have significant pricing power for the cross section of industry returns.

These results are robust to other specifications. Table 8 in the appendix presents the industry Fama-Macbeth results for the innovation factor and Fama-French 5 factors. In those tests, the market risk factor is the most significant, followed by the innovation risk factor (which is significant for equally-weighted portfolio returns but less so for value-weighted portfolio returns). None of the other factors are significant in either test. Table 9 in the appendix presents the Fama-Macbeth results for value-weighted individual stock returns. With respect to the three-factor model, the innovation factor is significant at the 10% level and has a t-statistic fairly similar in magnitude to that of two other factors, the excess market return and SMB. HML, however, is no longer significant with either specification. More formally, the test of whether HML is spanned by the RMRF, SMB, and innovation factors produces no significant intercept for HML and thus indicates that it is

	λ Values	
$High - Low$ $\frac{RD}{Inv}$	0.888* (1.83)	0.856** (2.35)
$Mkt - rf$	0.591*** (2.89)	0.425* (1.77)
HML	0.156 (0.97)	0.408** (2.15)
SMB	0.078 (0.48)	0.249 (1.27)
Weights	Value	Equal

Table 3: Fama-Macbeth Industry Results for Fama-French 3 Factors and Innovation Factor This table reports the Fama-Macbeth prices of risk from the two-stage Fama-Macbeth regression presented in the paper for value- and equal-weighted industry returns. Values reported as percentage points per month. First, for each industry at each point in time, 72-month rolling-window betas with respect to the innovation factor and simultaneously the Fama-French 3-factor model. After that, at each point in time, a cross-sectional regression of excess returns on betas is computed, and the prices of risk extracted as the λ values in specification (3). Specifically, each estimate reported is an estimate of a lambda value based on a time-series average of the lambdas estimated for each cross-sectional second-stage regression. Results robust to value vs. equal weighting of factors and different horizons for rolling window estimation. *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level. Numbers in parentheses are t-statistics corrected for autocorrelation over time.

spanned by the other three. In contrast, the innovation factor is not spanned by the three traditional Fama-French factors. For the five factor results, the innovation factor is significant at the 5% level. The same patterns from the 3-factor model are still apparent, namely that RMRF and SMB are significant but HML is not. Additionally, CMA is no longer significant (again indicating that this contrast between the composition of investment and the intensity of investment is important) and RMW has a negative price of risk.

Across all of these specifications, the key result is the consistent significance of the innovation factor, which indicates that the risk spanned by this factor is important for the entire cross-section of excess industry and stock returns, and that it is not spanned by the other factors in the Fama-French models. Second, adding the innovation factor seems to eliminate the explanatory power of HML for the cross-section of equity returns.

2.4 Evidence on Markups and Luxury Goods

The previous sections have clearly documented that high R&D/Investment firms earn not only higher equity returns, but also higher returns after accounting for the most common equity return factor model predictions. Rational asset pricing models imply that this must be a compensation for some form of risk which matters to investors, and the Fama-MacBeth results indicate that this risk matters not only for the returns of high R&D/Investment firms, but also for the entire cross-section of equity returns. Having documented this return pattern and the importance of the risk factor spanned by these high R&D/Investment firms, the goal is now to try to understand this risk factor and to link it to underlying economic quantities.

For this task it is helpful to think about why these firms do so much R&D relative to other forms of investment. Numerous theories for this have been advanced, but one that has received general acceptance is that R&D acts as a way for firms to maintain their competitive advantages. In particular, for firms that produce differentiated products and rely on being able to charge premiums for those products, one important way to maintain their differentiation and the willingness of consumers to pay premia is to continue to innovate. Indeed, the summary statistics confirm that firms which do more R&D relative to total investment charge higher price markups relative to cost (have a higher Revenue/Cost of Goods Sold ratio.) The results in Table 10 provide further stronger evidence on this point–the regression results of future markup on the ratio of R&D/Investment, firm size, and controls for industry and year fixed effects indicate a positive and significant effect of R&D/Investment on future firm markups. This evidence is also consistent with firm-level evidence by Cassiman and Vanormelingen (2013), who find that product innovations increase firm markups by an average of 5.1% and process innovations increase firm markups by 3.8% on average.

But why are higher markups in themselves more risky and why is this risk important to investors? One clue comes in the relation between the returns to the long-short R&D/Investment portfolio and the luxury sales index compiled by Ait-Sahalia et al. (2004). Table 11 shows that the growth in luxury good sales helps to explain the risk premium associated with this long-short portfolio, which indicates that the risk implied by the sale of luxury goods, another high markup item, is similar to that spanned by the R&D/Investment factor. In particular, the luxury consumption risk that

Ait-Sahalia and his coauthors identify seems to be linked to the risk of these high R&D/Investment firms. One can think of this more broadly as demand risks that affect all firms, but particularly firms which rely on being able to charge high markups, as both their prices and quantities are potentially more prone to shifts in consumer preferences. The next section builds on this key insight and introduces a model which formalizes this intuition.

3 Model Setup

The model features a number of different elements which will be described in this section. Its most novel feature is the integration of product market competition into a production-based asset pricing framework, as will be described later. The model is infinite horizon and discrete time and contains heterogeneous consumers, heterogeneous firms, and two state variables. The consumers, firms, and environment are described in the following subsections.

3.1 Consumers

Consumers in this model are the source of demand for the firms. Each period, a unit mass of consumers enters the market for a good and views the menu of options offered by firms. An option offered by a firm consists of a quality level of product and corresponding price, as will be discussed in greater detail later. For now, it suffices to say that quality is a feature which vertically differentiates products–that is, all consumers prefer a higher quality product, all else equal. Each consumer evaluates the menu of offerings and chooses the product that maximizes his utility. The consumer may choose to buy either one unit of one product or not to buy at all. What differentiates consumers is their willingness to pay for an increase in a product's quality.

Formally, the willingness of consumer j to pay for a higher quality product is represented by the parameter θ_j. The quality of products is indexed by s and the indirect utility that a consumer with preference parameter θ_j maximizes every period is given by:

$$U_j = \left\{ \begin{array}{cc} u_0 + \theta_j^s - p & \text{if purchase good of type s at price p} \\ 0 & \text{else} \end{array} \right\}$$

That is, consumers get some base utility from purchasing a product of any quality level u_0, then some utility which depends on both their preference for quality and the quality of the good they purchase. Finally, they internalize the price of the good which they purchase. This framework is a fairly standard one for vertically differentiated goods, see e.g. Tirole (1988). The consumers are price takers and so have no ability to impact prices; their decisions are independent of the decisions of the other consumers. Therefore the consumer's problem can be expressed as:

$$\underset{s_i}{max} \left\{ u_0 + \theta^{s_i} - p\left(s_i\right), 0 \right\} \tag{5}$$

The parameter θ is the only differentiating factor among consumers and thus what drives any differences in their decisions. In wanting to tie the distribution of θ to empirical counterparts, several options were considered. Existing evidence suggests that factors which derive heterogeneity across households include income, age, wealth, and other sources, but, for the purposes of this model, perhaps income is the most salient. The distribution of income has been extensively studied and researchers have suggested a number of different distributions to match the cross-sectional patterns of income, including the exponential distribution, the lognormal distribution, and the generalized Pareto distribution. Among these, the exponential is chosen in this paper because of its property as a distribution governed by one parameter. Given that there is no precise data counterpart to the preference parameter, the goal is to calibrate as close to the data as possible, and having relatively fewer parameters for the distribution of preferences helps achieve that goal. The results, however, are robust to the other distributions with similar properties.

The dynamics of the θ distribution vary over time in the model with one of the model's two state variables, X_t. This state variable can be interpreted as a demand or preference shock and it is set equal to the mean (or the inverse of the scale parameter) of the exponential distribution of θ. That is, higher values of X_t imply a distribution which skews more towards greater willingness to pay for quality, while lower values imply a distribution which skews more towards lower willingness to pay for quality, as illustrated in Figure 6. The log of X_t will follow an AR(1) process, given by equation (6).

$$x_{t+1} = (1 - \rho_x)\,\bar{x} + \rho_x x_t + \sigma_x \epsilon^x_{t+1} \tag{6}$$

where ϵ^x_{t+1} is a standard normal random variable. The parameters for this process can be directly tied down by the aggregate markups in the model economy, as will be discussed in the calibration section.

3.2 Firms and Good Quality

The other type of agent in the economy is a firm. Firms will produce the goods and will face constraints on their production from both consumer demand and the supply and productivity of capital. Firms will maintain two types of capital–intangible and physical–which will affect their profits and values differentially. Finally, firms will be heterogeneous, with a sufficient statistic for firm heterogeneity being the quality level of products that they produce. Firms will choose both their quality level and the price which they set for their goods, and this will determine their capital needs and profit.

At any given point in time, firms maintain two stocks of capital. One is physical capital K_t, which is required for production. Production follows a standard AK-technology, where total output Y_t can be represented as $Y_t = A_t K_t$ and A_t represents the state of capital productivity in the economy. A_t is the second state variable in this model and again its log follows an AR(1) process, displayed in equation (7).

$$a_{t+1} = (1 - \rho_a)\,\bar{a} + \rho_a a_t + \sigma_a \epsilon^a_{t+1} \tag{7}$$

where ϵ^a_{t+1} is a standard normal random variable uncorrelated with ϵ^x_{t+1}. Firms also maintain levels of intangible capital IK_t. Unlike physical capital, intangible capital is not used directly in the production process. Rather, it helps to differentiate products. Specifically, firms that maintain higher levels of intangible capital relative to their total capital produce higher quality products. For a firm i with capital levels K_{it} and IK_{it}, the quality of goods that it produces is $s_{it} = \frac{IK_{it}}{IK_{it}+K_{it}}$. The intuition for this feature is as follows: physical capital is needed for the actual production of products, but intangible capital helps to differentiate goods. The more intangible capital, in the form of research, thought, innovation, testing, process development, etc. that goes into the product, the higher the quality that the product will be and the more that consumers will be willing to pay for it. This will also help match the empirical finding that firms that do more R&D/Investment charge higher markups over cost for their products. One could akternatively envision N production functions for goods of different qualities requiring certain ratios of physical and intangible capital. Such a setting would be isomorphic to this one, and the flexibility of the setup allows for a wide range of interpretation of R&D expenses.

There are a finite number of quality levels s_1, s_2, ... s_N at which a product can produced, evenly spaced throughout the unit interval that defines the quality spectrum. The economy features N firms; at time 0, firm i is born into quality level s_i. That is, at time 0, there is exactly one firm per quality level. As long as this continues to be the case, this single firm acts a monopolist in the market for goods of that specific quality level. Of course, the prices that such a firm can set will be constrained by the prices set by other firms, but this firm can earn positive profits. If multiple firms are producing the same quality product, however, these firms will engage in Bertrand competition and their profits will both be 0. While there is no firm entry, firms are able to endogenously choose their quality level and switch into any of the N good quality markets. As Proposition 1 states (and Appendix B proves), as long as there is some positive switching cost c, this will never happen in the Pareto efficient Nash equilibrium.[1]

Proposition 1. *If there is a positive cost of switching quality levels, no firm will ever switch from its initial quality level in the Pareto efficient Nash equilibrium.*

[1] This result is similar to that in Chapter 3 of Grossman and Helpman: "Innovation and Growth in the Global Economy".

Firms rent their physical and intangible capital at rental rates r_K and r_{IK} respectively. One could view this as resulting from the inelastic supply of these two inputs from an unmodeled section of the economy. One could also alternatively think of firms owning their capital and being able to freely adjust it intro-period after observing the aggregate state variables. In that case the costs of capital would be the difference between the price paid today and the discounted depreciated amount for which it can be sold in the following period and so would be stochastic. The quantitative results of the model, however, do not change under this formulation.

3.3 Final Goods Market and Firm Problem

Figure 3 illustrates the interactions of consumers and firms in the market for final goods.

Every period, each firm (representing one of the N different quality levels) decides on a price to set for its product after observing the realizations of the two state variables. Based on that price and the prices and qualities set by all of the other firms, consumers will choose the product offering which maximizes their utility. The aggregation of consumers who choose a particular product will determine the quantity demanded for that product. In equilibrium, firms will know this quantity, and so will rent the exact amount of physical and intangible required to product that many units of their quality level.

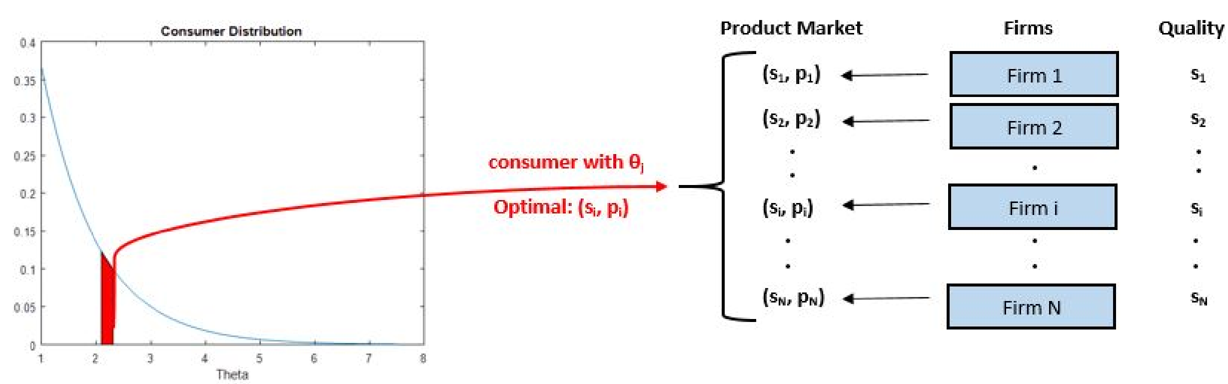

Figure 3: Interaction of Consumers and Firms in Product Market

Each firm will set its price taking into account its own quality level and those of other firms, as well as its beliefs about the prices that the other firms set (which will be correct in equilibrium). It will account for the two aggregate states in the economy, A_t and X_t, and the decision-making problem of the consumers. Since capital is adjustable each period, firms will incorporate the cost of capital into their pricing decision, and, by choosing the price they set (and thus the quantity they will sell), they also choose their optimal capital levels. As a result, the solution methodology does not require tracking the capital distribution of firms over time. The firm's problem can thus be written as maximizing profit given in equation (8) subject to the demand constraint in equation (9).

$$\pi_{it}\left(A_t, L_t, s_i\right) = \max_{P_{it}, s_i} \left\{ P_{it} A_t K_{it} - r_K K_{it} - \underbrace{\frac{r_{IK} s_i K_{it}}{(1-s_i)}}_{r_{IK} I K_{it}} - c 1_{\{\text{switch}\}} \right\} \tag{8}$$

$$\text{s.t. } A_t K_{it} = \int 1_{\{argmax(U_j)=s_i\}} f\left(j\right) dj \tag{9}$$

where the latter conditions enforces that firms produce exactly enough to meet the quantity demanded. (One could also make this last equality a weak inequality and have firms maximize over their capital stocks, but it is clear that no firm would want to rent more capital than required to meet its demand.)

3.4 Firm Value

Firms are entirely equity financed and earn profits that are weakly greater than 0 every period. As a result, the value of a firm is simply its discounted dividend stream, where the dividends are equal to the profits earned by a firm in a given period. Firm value V_t can be expressed as:

$$V_{it}\left(A_t, X_t, s_i\right) = \pi_{it} + E_t\left[M_{t+1} V_{it+1}\right] \tag{10}$$

where M_{t+1} represents the stochastic discount factor in the economy. This discount factor has exposures to both shocks A_t and X_t, as well as time-varying prices of risks for both shocks. M_{t+1} is thus given by equations (11) - (13).

$$log\left(M_{t+1}\right) = log(\beta) + \gamma_{at}\left(a_t - a_{t+1}\right) + \gamma_{xt}\left(x_t - x_{t+1}\right) \tag{11}$$

$$\gamma_{at} = \gamma_{a0} + \gamma_{a1}\left(a_t - \bar{a}\right) \tag{12}$$

$$\gamma_{xt} = \gamma_{x0} + \gamma_{x1}\left(x_t - \bar{x}\right) \tag{13}$$

4 Model Calibration and Results

4.1 Model Calibration

Despite the novel product market dynamics in the model, the number of parameters to calibrate is quite limited. The model contains 13 parameters and is calibrated on a monthly basis. The parameters can be grouped into four categories: the SDF parameters β, γ_{a0}, γ_{a1}, γ_{x0}, and γ_{x1}, the rental rates r_K and r_{IK}, and the parameters governing the productivity shock $\bar{a}$, σ_a, and ρ_a and those governing the preference shock $\bar{x}$, σ_x, and ρ_x.

Two groups of these parameters can be estimated directly from the data. First, the rental rates are tied to the rates of depreciation on the two forms of capital, as discussed in Section 3. Thus, these monthly parameters can be tied to the annual depreciation rates of physical and intangible capital found in Lin (2012). Lin finds the rate of depreciation on tangible capital to be 0.1 and the rate of depreciation on intangible capital to be 0.2. Given that these rental rates also reflect some cost of discounting, the monthly rental rates for tangible and intangible capital are set at 0.01 and 0.02, respectively. Second, the parameters governing the productivity shock are standard in much of this literature and have been estimated and used by a number of papers. This paper follows the calibration in Zhang (2005) for the monthly AR(1) process governing productivity shocks.

This leaves two sets of parameters which have to be calibrated. The first is the set of three parameters governing the demand shock process. Given the difficulty of observing this process directly in the data, the challenge is to find a readily observable empirical series to which the demand shock can be closely linked. In this model, given the previous two sets of parameters, the demand shock determines the markups set by each firm. Thus, one can directly link the demand shock to the aggregate markup that this model produces. Fortunately, Kung, Schmid, and Corhay (2015) have estimated an AR(1) process for the aggregate price markup series, and so this paper calibrates the demand shock process to most closely match the parameters that they estimate. The values for the parameters in the paper can be found in Table 12 and the resulting values for the aggregate markup process in Table 13.

The last set of parameters is the one governing the SDF. There are five parameters in the SDF, and thus one needs at least five data counterparts with which to identify these parameters. This paper follows the lead of Zhang (2005) in taking three of these data counterparts to be the mean and volatility of the risk-free rate and the Sharpe ratio of the market portfolio. The remaining two parameters are used to target the returns to low R&D/Investment firms and the returns to high R&D/Investment firms. All of the estimated parameters can be found in Table 12, while the risk-free rate and market return moments can be found in Table 13. The returns to high and low R&D/Investment firms will be discussed in the next section.

4.2 Model Results

The most novel feature of the model is the product market dynamic and thus it makes sense to start there. While the effects of the productivity shock are fairly standard, the effects of the consumer preference shock are perhaps not so readily understood. One way to understand the effects of these shocks is to look at their impacts on the decisions which consumers make. Figure 4 illustrates the effect of a shock to preference on consumer decisions.

The graph on the left represents the distribution of consumers under the median state of consumer preference, while the graph on the right represents the distribution of consumers following a positive preference shock. The x-axis displays the θ parameter of consumers while the y-axis gives the density (which integrates to 1 in both cases.) Ignoring the colors, one notices that the distribution shifts towards higher θ values following a positive preference shock. What is more interesting is the effect that this has on the product choice of consumers. The colors on the graph represent the product choices that consumers make, going from red (lowest quality) to magenta (highest quality). One sees that consumers shift significantly towards higher quality products following a positive preference shock and shift away from products of lower qualities. Figure 7 shows that this example is consistent with the global behavior of the model: the higher the preference parameter, the lower the market shares of low-quality products and the higher the market shares of high quality products. This is in keeping with one's intuition: as consumers' tastes shift more towards higher quality, we should see the market shares of these companies growing.

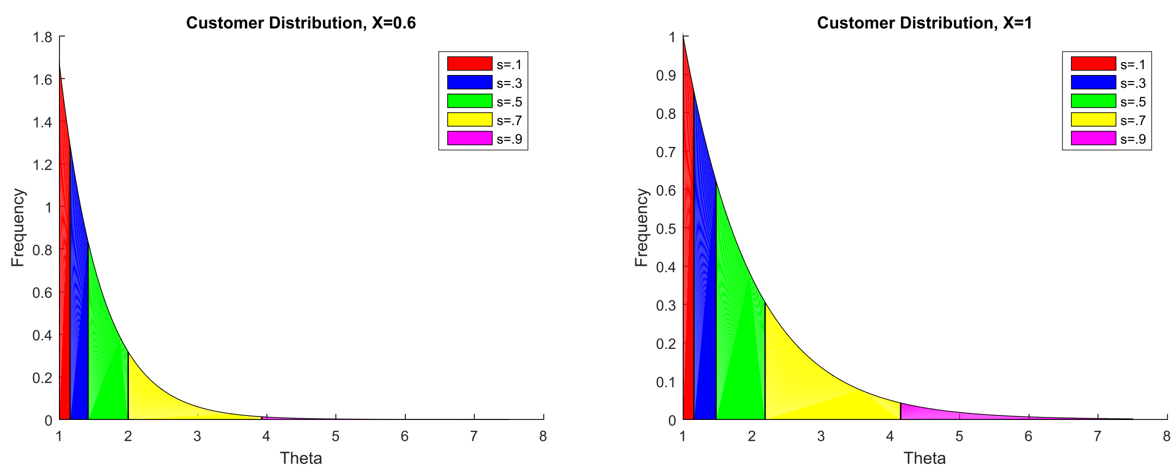

Figure 4: Effect of a Shock to Consumer Preferences on Decisions and Quantities X represents the aggregate demand state of the economy, while theta represents the preference parameter of a consumer

The other component to the firm's profits, besides its market share, is its profit margin, or the amount of profit that it earns for every unit that it sells. Figure 8 plots the profit margins of low-, medium-, and high-quality firms as a function of the underlying preference state. Consistent with empirical evidence (see e.g. Nekarda and Ramey (2013)), markups are fairly insensitive to demand shocks. However, the markups of high-quality firms are more procyclical with respect to demand shocks than those of low- or medium-quality firms, whose markups are essentially acyclical. Combined with the differential exposures of quantities to demand shocks, this implies that the profits (cash flows) of high-quality firms covary much more positively with demand shocks than do those of low-quality firms, whose cash flows covary somewhat negatively with demand shocks.

This hetereogeneous exposure to demand shocks is key for the asset pricing implications of the paper. Firms of all qualities have similar exposures to productivity shocks. This is because a positive productivity shock reduces the amount of capital required to produce a certain amount of output, which also reduces the amount of intangible capital required. The former effect is more significant for low-quality firms and the latter is more significant for high-quality firms, but, on balance, the total effects are similar. What differentiates firms, then, is their exposure to the demand shock. Since both shocks are priced by investors, the similar loading of all firms to the productivity shock will drive a risk factor which is essentially common to all firms. In a CAPM sense, this will be the risk factor that the market prices. The covariance with respect to the demand shock will be a priced risk factor whose quantity of risk differs significantly across firms, and this is what will drive the heterogeneity in returns. Since the high-quality firms are more exposed to this shock, they will earn higher returns in equilibrium.

This result is consistent with the earlier empirical evidence on the reliance of these firms on markups and the comovement of their returns with the growth of luxury sales. It is precisely these quantities that are most directly tied to preference shocks as those shocks most strongly affect whether consumers purchase high-markup products and are willing to pay high premia for them. It should thus not be surprising that this risk factor also drives the higher returns of R&D-intensive firms that are also dependent on markups.

Table 14 presents the models results on returns and firm size. The model matches the CAPM alpha and beta results fairly well. In addition, despite not being calibrated to match firm sizes, the product market implications for firm size match the empirical distribution of firm size by ratio of R&D/Investment closely. High R&D/Investment firms tend to be smaller and to earn higher CAPM alphas despite their slightly higher CAPM betas. The fact that these firms are smaller on average is important for the model. Since the magnitude of the covariance of these firms' cash flows with the demand shock is much higher than the magnitude of the covariance for the lower R&D/Investment firms, one needs that these firms account for less of the market value than the low R&D/Investment firms in order for the value-weighted market portfolio to have minimal exposure to the demand shocks. Finally, the model does not match the Fama-French 3 or 5 factor models simply because there are not enough shocks in the model to capture asset pricing cross-sectional heterogeneity on more than two dimensions, but this is an interesting area for future research.

5 Conclusion

This paper focuses on the returns to this innovation at the firm level by proposing a novel characteristic that examines the fraction of investment attributed to R&D expenses. This metric is important for the entire cross-section of firms, including larger, more economically significant firms. The asset pricing implications examine how risk and returns vary with the composition of investment chosen by a firm.

Relative to the Fama-French 3-factor model, a portfolio which goes long the highest R&D/Investment firms and short the lowest R&D/Investment firms earns monthly excess returns of 58bps per month, or just over 7% annually. This is after accounting for the fact that these high R&D/Investment firms have slightly higher betas and tend to be small, growth firms. These results are significant at the 1% level, and, in contrast to previous studies on R&D, hold for value-weighted portfolios. Compared to the Fama-French 5-factor model, the results are even more significant: the long-short portfolio earns risk-adjusted returns of 82bps per month, which corresponds to over 10% per annum. The main reason for the difference in the results is that these high-R&D firms load more negatively on the Fama-French profitability factor, despite earning higher revenues relative to both costs and tangible capital. The risk spanned by these high R&D/Investment firms is not just important for those firms, however. In the Fama-MacBeth test, the long-short portfolio has significant explanatory power for the entire cross-section of excess returns and (along with the market and SMB factors) spans HML such that it is no longer significant. Combined, these results indicate very strongly that high R&D/Investment firms are earning significantly higher returns than those predicted by the leading models of expected returns, and that the risk spanned by these firms is important for the entire cross-section of equity returns.

In seeking to explain this pattern, this paper focused on the exposure of these firms to the high markups which they charge. There is significant evidence that high R&D/Investment firms charge significantly higher markups over cost, even after controlling for industry, size, and year effects. Moreover, the excess returns of these firms correlate significantly with the sales growth of another high-markup item, luxury goods. This effect holds even after controlling for the usual Fama-French factors. Combined, these pieces of evidence suggest that the risk encapsulated by the sales of these high-markup products is important to understand the higher returns of R&D-intensive firms.

The final contribution of this paper is a model which formalizes this intuition. The model integrates a standard production-based asset pricing framework with the novel mechanism of product market interactions between heterogeneous firms and heterogeneous consumers. In the product (final goods) market, heterogeneous firms offer vertically differentiated products to consumers with different levels of willingness to pay for higher quality products. The equilibrium between these two agents results in the purchase of lower-quality goods by consumers who are less willing to pay for quality and the purchase of higher-quality goods at higher markups by consumers who are more willing to pay for quality. The aggregation of consumers choosing a particular firm's product determines the quantity that it decides to produce, but this quantity (and the price that the firm sets) are subject to both supply shocks in the form of productivity shocks and demand shocks in the form of changes to the distribution of consumer preferences. While firms have similar exposures to supply shocks, the model generates the endogenous result that firms offering higher-quality products are more exposed to demand shocks. This risk factor is not spanned by the market risk factor and thus generates excess returns for these firms. The model also matches the size distribution of firms and the markup dynamics of the economy.

While these targets are certainly first-order, one could imagine many other goals for such a model in capturing the dynamics of more sophisticated return models or matching firm leverage or investment timing choices more closely. This product market mechanism seems to be a good first step on the path towards these goals, which are left for future research.

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Appendix A: Tables and Figures

Table 4: Summary Statistics

	R&D/Investment				
	0-0.2	0.2-0.4	0.4-0.6	0.6-0.8	0.8-1
Assets ($MM)	4344	2280	2491	1444	448
Leverage (%)	25.3	23.2	20.3	14.8	19.6
PPE/Assets (%)	38.9	28.0	22.0	16.2	10.8
Revenue/Cogs (%)	159.3	169.5	192.0	239.5	246.5
Revenue Growth (%)	21.1	21.1	26.1	33.2	32.9
Revenue/PPE	4.75	6.27	7.73	10.2	16.4
Revenue/Assets	1.19	1.23	1.14	1.02	0.79
Capex/Assets (%)	9.86	7.27	6.02	4.91	2.38
R&D/Assets (%)	0.98	3.15	6.14	12.1	32.9
R&D/Investment (%)	0.10	0.30	0.50	0.70	0.92

Note: Table presents mean of each variable by R&D/Investment group. All variables or ratios winsorized at the 1% and 99% levels. Firm-year observation level.

Table 5: R&D/Investment Transition Matrix

% of R&D/Inv obs		Time $t+1$ R&D/Inv Decile									
		1	2	3	4	5	6	7	8	9	10
Time t R&D/Inv Decile	1	98.1%	0.5%	0.5%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%
	2	3.4%	65.4%	25.3%	3.1%	1.2%	0.6%	0.1%	0.5%	0.2%	0.2%
	3	1.3%	6.7%	67.0%	17.3%	4.1%	1.7%	0.9%	0.5%	0.3%	0.3%
	4	0.6%	0.7%	17.4%	50.8%	19.4%	6.1%	2.3%	1.5%	0.9%	0.4%
	5	0.4%	0.3%	3.7%	21.0%	43.4%	18.1%	7.3%	3.3%	1.7%	0.8%
	6	0.3%	0.1%	1.4%	5.7%	20.4%	37.6%	20.4%	8.3%	4.1%	1.8%
	7	0.3%	0.1%	0.9%	2.3%	6.9%	21.4%	33.7%	20.8%	9.9%	3.8%
	8	0.1%	0.1%	0.5%	1.2%	3.1%	8.7%	22.2%	34.3%	21.6%	8.2%
	9	0.3%	0.1%	0.4%	0.8%	1.7%	4.1%	9.3%	22.8%	38.5%	22.1%
	10	0.4%	0.0%	0.3%	0.5%	0.9%	1.7%	3.6%	8.0%	22.3%	62.2%

Note: Annual transition matrix for R&D/Investment deciles. Value in ij^{th} entry represents the probability that a firm in the i^{th} R&D/Investment decile in year t is in the j^{th} decile in year $t+1$. Firm-year observation level.This measure is significantly more persistent than the book-to-market, profitability, investment, and momentum measures. Numbers in each row sum to 100% (with possible rounding error).

Table 6: Equal-Weighted vs. Value-Weighted Results for Other R&D Measures

Equal-weighted:

Alphas	1	2	3	4	5	6	7	8	9	10	10-1
					R&D/Sales						
α	-0.094	-0.039	0.075	0.113	0.310	0.297	0.394	0.428	0.282	0.269	0.364*
	(-1.05)	(-0.48)	(0.90)	(1.35)	(3.17)	(2.61)	(3.12)	(3.10)	(1.77)	(1.36)	(1.81)
					R&D Capital/Market Equity						
α	-0.436	-0.189	-0.142	-0.013	-0.069	0.170	0.217	0.356	0.712	1.381	1.817***
	(-5.08)	(-2.78)	(-1.93)	(-0.18)	(-0.82)	(1.79)	(2.00)	(2.67)	(4.25)	(6.15)	(7.89)
					R&D/R&D Capital						
α	0.455	0.431	0.350	0.251	0.331	0.177	0.108	0.148	-0.217	-0.102	-0.691***
	(2.94)	(3.46)	(3.95)	(2.96)	(4.12)	(1.97)	(1.11)	(1.10)	(-1.73)	(-0.55)	(-4.08)

Value-weighted:

Alphas	1	2	3	4	5	6	7	8	9	10	10-1
					R&D/Sales						
α	-0.010	0.040	-0.040	0.025	0.086	0.084	-0.003	0.413	0.416	0.055	0.154
	(-0.92)	(0.46)	(-0.42)	(0.28)	(0.98)	(0.92)	(-0.03)	(3.12)	(2.53)	(0.27)	(0.62)
					R&D Capital/Market Equity						
α	-0.013	0.003	0.160	0.198	0.134	0.095	0.194	0.145	0.087	0.092	0.105
	(-0.12)	(0.03)	(1.94)	(2.23)	(1.46)	(0.95)	(1.72)	(1.14)	(0.63)	(0.63)	(0.55)
					R&D/R&D Capital						
α	-0.003	0.178	0.092	0.121	0.023	0.108	0.168	0.052	0.084	-0.001	-0.144
	(-0.03)	(1.92)	(1.21)	(1.60)	(0.29)	(1.06)	(1.60)	(0.38)	(0.57)	(-0.01)	(-0.61)

Note: Tables present Fama-French 3-factor equal- and value-weighted alphas sorted by deciles of common R&D measures in the literature. Alphas are reported as basis points (bps) per month. In the last column, *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level. These results use the same data sample and portfolio construction methodology as the R&D/Investment results presented in the paper. Numbers in parentheses are Newey-West t-statistics.

Table 7: Equal-Weighted R&D/Investment Results

	R&D/Investment Decile							
	0	1	2	4	6	8	10	10-1
α	-0.130	-0.258	-0.132	0.049	0.266**	0.429***	0.767***	1.025***
	(-1.17)	(-2.84)	(-1.59)	(0.60)	(2.60)	(3.19)	(3.85)	(5.27)
$RMRF$	0.993	1.090	1.059	1.062	1.066	1.045	1.049	-0.041
HML	0.408	0.333	0.323	0.087	-0.225	-0.333	-0.297	-0.630
SMB	0.895	0.569	0.651	0.746	0.948	1.158	1.557	0.988

Note: Table reports Fama-French 3-factor equal-weighted alphas and betas by deciles of R&D/Investment measure. Alphas are reported as basis points (bps) per month. In the top row, *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level. These results use the same data sample and portfolio construction methodology as the value-weighted results presented in the paper. Numbers in parentheses are Newey-West t-statistics.

Table 8: Industry Fama-Macbeth Results for Fama-French 5 Factors and Innovation Factor

	λ Values	
$High - Low$ $\frac{RD}{Inv}$	0.599	0.658*
	(1.32)	(1.87)
$Mkt - rf$	0.594***	0.551**
	(2.91)	(2.34)
HML	0.126	0.249
	(0.79)	(1.39)
SMB	0.063	0.242
	(0.39)	(1.29)
RMW	-0.076	-0.163
	(-0.60)	(-1.20)
CMA	0.174	0.223
	(1.50)	(1.66)
Weights	Value	Equal

Note: This table reports the Fama-Macbeth prices of risk from the two-stage Fama-Macbeth regression presented in the paper for value- and equal-weighted industry returns. Values reported as percentage points per month. First, for each industry at each point in time, 72-month rolling-window betas with respect to the innovation factor and simultaneously the Fama-French 5-factor model. After that, at each point in time, a cross-sectional regression of excess returns on betas is computed, and the prices of risk extracted as the λ values in specification (4). Specifically, each estimate reported is an estimate of a lambda value based on a time-series average of the lambdas estimated for each cross-sectional second-stage regression. Results robust to value vs. equal weighting of factors and different horizons for rolling window estimation. *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level. Numbers in parentheses are t-statistics corrected for autocorrelation over time.

Table 9: Individual Stock Fama-Macbeth Results

	λ Values	
$High - Low$ $\frac{RD}{Inv}$	0.474*	0.520**
	(1.84)	(2.05)
$Mkt - rf$	0.405**	0.397**
	(2.12)	(2.08)
HML	0.035	0.047
	(0.26)	(0.37)
SMB	0.336**	0.327**
	(2.43)	(2.42)
RMW		-0.193**
		(-2.06)
CMA		0.102
		(1.15)

Note: This table reports the Fama-Macbeth prices of risk from the two-stage Fama-Macbeth regression presented in the paper for value-weighted stock returns. Values reported as percentage points per month. First, for each stock at each point in time, 60-month rolling-window betas with respect to the innovation factor and simultaneously the Fama-French 3-factor model or the Fama-French 5-factor model. After that, at each point in time, a cross-sectional regression of excess returns on betas is computed (again, separate regressions for the 3 factors and R&D from the 5 factors and R&D), and the prices of risk extracted as the λ values in specifications (3) and (4). Specifically, each estimate reported is an estimate of a lambda value based on a time-series average of the lambdas estimated for each cross-sectional second-stage regression. *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level. Numbers in parentheses are t-statistics corrected for autocorrelation over time.

Table 10: R&D/Investment and Firm Markup

	$Markup_{t+1}$
$\frac{RD_t}{Inv_t}$	0.424***
	(3.20)
$ln(Assets_t)$	0.048
Industry FE	Yes
Year FE	Yes
Obs.	129,097

Note: Markup is defined as Revenue/Cost of Goods Sold -1. *** indicates significant at the 1% level. Numbers reported in parantheses are standard errors clustered at industry level. All variables or ratios winsorized at the 1% and 99% levels. Firm-year observation level.

Table 11: R&D/Investment Returns and Luxury Good Sales

	$ret_{1,t}$	$ret_{10,t}$	$ret_{10-1,t}$
L_t	-0.278	0.664*	0.942**
	(-1.48)	(1.82)	(2.41)
$RMRF_t$	0.860	1.194	0.334
HML_t	0.209	-0.714	-0.923
SMB_t	-0.102	1.247	1.348
Intercept	-0.114	0.491	0.605
Obs.	192	192	192
$Overall-R^2$	75.32	79.64	69.23

Note: L_t measure is real growth in luxury sales from Ait-Sahalia et al. (2004). ret_{10} represents the value-weighted return on the firms in the highest R&D/Investment decile. The coefficient can be interpreted as follows: a 1 standard deviation increase in luxury good sales is associated with a 66 bps increase in the monthly returns of the high R&D/Investment portfolio and a 28 bps decrease in the monthly returns of the low R&D/Investment portfolio, after controlling for the exposure of this portfolio to the Fama-French 3 factors. For L_t, * indicates significant at the 10% level. Numbers reported in parantheses are Newey-West standard errors. Firm-year observation level.

Table 12: Calibrated Parameters

Parameter	Value	Moment/Target
β	-0.006	r_f mean
γ_{a0}	35	r_f std dev
γ_{a1}	-700	r_M Sharpe
γ_{x0}	.5	r_{HI} mean
γ_{x1}	-10	r_{LO} mean
r_k	0.01	physical cap dep
r_{ik}	0.02	intangible cap dep
ρ_a	0.998	
μ_a	0	Zhang (2005)
σ_a	0.002	
ρ_x	0.998	Markup series ρ
μ_x	1.0	Markup series μ
σ_x	0.06	Markup series σ

Note: Calibration is at a monthly frequency. See discussion in Section 4.1.

Table 13: Model vs. Data Moments

Moment	Model	Data	Source
r_f mean	0.022	0.018	Campbell (2001)
r_f std dev	0.029	0.030	Campbell (2001)
r_M Sharpe	0.41	0.43	Campbell (2001)
Markup series ρ	0.99	0.9	Corhay, Kung, Schmid (2015)
Markup series μ	0.1413	0.1339	Corhay, Kung, Schmid (2015)
Markup series σ	0.0306	0.0230	Corhay, Kung, Schmid (2015)

Note: See discussion in Section 4.1. Return moments are presented on a monthly basis as in Zhang (2005) while markup moments are presented at a quarterly frequency as in Corhay, Kung, and Schmid (2015).

Table 14: Model Predictions for Returns and Size

	CAPM Results			
	α		β	
	Model	Data	Model	Data
Low R&D/Inv	-0.007	-0.016	1.001	0.925
Medium R&D/Inv	0.11	0.084	0.993	1.074
High R&D/Inv	0.18	0.271	1.065	1.270

	Size		
	Model	Data	
Low R&D/Inv	9.04	9.24	
Medium R&D/Inv	3.26	5.68	
High R&D/Inv	1	1	(normalized)

Note: Firms divided into three categories by level of R&D/Investment in both data and model. Size measured as Net PP&E. Alphas are reported as basis points (bps) per month. Model moments taken as mean of 1,000 samples of 600 observations, data counterparts also use 600 observations.

Table 15: Doublesorts on Firm Size and R&D Measures

FF3-Alpha		R&D/Investment Quintile					
		1	2	3	4	5	5-1
Assets Quintile	1	-0.652	-0.337	-0.125	-0.259	0.126	0.778***
		(-3.73)	(-1.70)	(-0.56)	(-1.02)	(0.44)	(2.57)
	2	-0.417	0.175	0.341	0.028	0.133	0.550**
		(-2.65)	(1.17)	(1.63)	(0.20)	(0.69)	(2.26)
	3	-0.225	-0.089	0.565	0.423	0.433	0.658***
		(-1.59)	(-0.71)	(3.67)	(2.76)	(2.68)	(3.22)
	4	-0.212	0.091	0.019	0.119	0.558	0.770***
		(-1.96)	(0.75)	(0.17)	(1.00)	(4.35)	(4.60)
	5	-0.047	-0.057	0.045	0.017	0.438	0.484***
		(-0.45)	(-0.64)	(0.51)	(0.19)	(4.94)	(3.08)

FF3-Alpha		R&D/Market Equity Quintile					
		1	2	3	4	5	5-1
Assets Quintile	1	-0.909	-0.140	-0.079	0.350	0.894	1.782***
		(-4.35)	(-0.62)	(-0.40)	(1.53)	(2.91)	(4.99)
	2	0.039	0.255	-0.185	0.236	0.602	0.563*
		(0.22)	(1.76)	(-1.29)	(1.44)	(2.66)	(1.96)
	3	0.265	0.238	0.364	0.299	0.428	0.164
		(1.70)	(1.80)	(2.66)	(2.17)	(2.56)	(0.73)
	4	0.229	0.158	0.091	0.172	0.245	0.016
		(1.78)	(1.52)	(0.85)	(1.43)	(1.30)	(0.07)
	5	0.032	0.236	0.058	0.052	0.029	-0.004
		(0.37)	(3.23)	(0.68)	(0.50)	(0.23)	(-0.02)

Note: Firms sorted first into quintiles on Assets and then on quintiles based on R&D measures. Table reports Fama-French 3-factor value-weighted alphas by group. Alphas are reported as basis points (bps) per month. In the last column, *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level. These results use the same data sample and portfolio construction methodology as the value-weighted results presented in the paper. Numbers in parentheses are Newey-West t-statistics. Insignificance of factor for higher asset quintiles is similar for most other existing R&D measures, including R&D Capital/Market Equity and R&D/R&D Capital.

Table 16: R&D/Investment and R&D/Market Equity Similarity Matrix

% of R&D/Inv obs		R&D/Market Equity Decile									
		1	2	3	4	5	6	7	8	9	10
R&D/Inv Decile	1	51.06%	19.51%	9.28%	5.14%	3.13%	2.31%	2.01%	1.80%	1.99%	3.78%
	2	20.92%	24.30%	17.67%	12.27%	7.90%	5.25%	3.44%	2.43%	1.76%	4.06%
	3	9.10%	17.45%	18.17%	15.51%	12.25%	9.44%	6.43%	4.50%	3.04%	4.11%
	4	5.21%	11.26%	14.83%	15.07%	13.89%	12.00%	9.49%	6.90%	4.89%	6.46%
	5	3.70%	8.11%	11.14%	13.06%	14.03%	13.44%	11.87%	10.28%	7.71%	6.66%
	6	3.04%	5.96%	8.78%	10.90%	12.74%	13.58%	13.94%	12.49%	10.63%	7.96%
	7	2.14%	4.42%	6.90%	9.13%	11.33%	12.97%	14.17%	14.86%	13.81%	10.26%
	8	1.77%	3.92%	5.50%	7.86%	9.56%	11.55%	13.79%	15.39%	17.54%	13.11%
	9	1.46%	2.84%	4.28%	5.84%	7.95%	10.44%	13.52%	16.44%	19.34%	17.90%
	10	1.89%	2.72%	4.07%	5.74%	7.49%	9.24%	11.38%	14.69%	18.93%	23.86%

Note: Value in ij^{th} entry represents the probability that a firm in the i^{th} R&D/Investment decile in year t is in the j^{th} R&D/Market Equity decile in year t. Firm-year observation level. Numbers in each row sum to 100% (with possible rounding error).

Table 17: R&D/Investment and R&D/Sales Similarity Matrix

% of R&D/Inv obs		R&D/Sales Decile									
		1	2	3	4	5	6	7	8	9	10
R&D/Inv Decile	1	64.61%	20.71%	8.06%	3.14%	1.60%	0.62%	0.35%	0.23%	0.33%	0.34%
	2	22.51%	35.18%	19.68%	11.26%	5.21%	2.73%	1.35%	0.85%	0.66%	0.58%
	3	6.67%	23.00%	27.07%	19.43%	9.73%	6.04%	3.24%	2.13%	1.57%	1.11%
	4	2.42%	10.17%	20.65%	23.00%	17.91%	11.12%	6.41%	3.92%	2.73%	1.67%
	5	1.34%	4.59%	10.655	17.78%	20.22%	17.15%	12.06%	8.07%	5.08%	3.07%
	6	0.48%	2.27%	5.39%	10.84%	17.45%	19.24%	17.66%	13.64%	8.37%	4.65%
	7	0.30%	1.24%	3.16%	6.06%	12.10%	16.86%	19.65%	19.50%	14.45%	6.68%
	8	0.10%	0.54%	1.82%	3.50%	7.35%	13.18%	19.28%	22.11%	20.77%	11.25%
	9	0.10%	0.40%	1.05%	2.54%	4.78%	8.65%	13.54%	19.39%	25.64%	23.91%
	10	0.25%	0.34%	0.84%	1.62%	2.52%	3.79%	6.31%	10.67%	22.27%	51.37%

Note: Value in ij^{th} entry represents the probability that a firm in the i^{th} R&D/Investment decile in year t is in the j^{th} R&D/Sales decile in year t. Firm-year observation level. Numbers in each row sum to 100% (with possible rounding error).

Table 18: R&D/Investment and R&D Capital/Market Equity Similarity Matrix

% of R&D/Inv obs		R&D Capital/Market Equity Decile									
		1	2	3	4	5	6	7	8	9	10
R&D/Inv Decile	1	45.11%	19.88%	10.98%	6.60%	3.96%	2.73%	2.43%	2.33%	2.32%	3.65%
	2	19.42%	21.59%	17.23%	13.44%	9.21%	6.14%	4.19%	2.72%	1.89%	4.16%
	3	9.47%	16.09%	16.63%	14.63%	12.79%	10.45%	7.36%	5.13%	3.35%	4.10%
	4	6.58%	10.43%	13.43%	13.98%	13.55%	12.07%	10.18%	7.73%	5.45%	6.60%
	5	4.96%	8.19%	10.76%	12.52%	12.94%	13.04%	12.11%	10.22%	8.41%	6.86%
	6	4.33%	6.77%	8.82%	10.34%	11.83%	12.66%	13.54%	12.67%	10.76%	8.29%
	7	3.14%	5.54%	7.28%	9.09%	10.80%	12.21%	13.36%	14.17%	13.94%	10.45%
	8	2.84%	4.56%	6.00%	7.78%	9.35%	11.34%	13.35%	15.26%	16.72%	12.79%
	9	2.20%	3.84%	4.88%	6.41%	8.30%	10.38%	12.44%	15.32%	18.34%	17.88%
	10	2.39%	3.63%	4.61%	5.72%	7.58%	9.18%	10.99%	14.05%	18.41%	23.43%

Note: Value in ij^{th} entry represents the probability that a firm in the i^{th} R&D/Investment decile in year t is in the j^{th} R&D Capital/Market Equity decile in year t. R&D Capital calculated as $\sum_{\tau=t-5}^{t} (1 - .2 * (t - \tau)) RD_{\tau}$. Firm-year observation level. Numbers in each row sum to 100% (with possible rounding error).

Table 19: R&D/Investment and R&D/R&D Capital Similarity Matrix

% of R&D/Inv obs		R&D/R&D Capital Decile									
		1	2	3	4	5	6	7	8	9	10
R&D/Inv Decile	1	18.17%	11.07%	10.29%	8.42%	7.57%	7.50%	8.35%	8.18%	12.01%	8.43%
	2	10.99%	10.27%	12.17%	10.68%	10.82%	9.79%	9.61%	8.25%	11.20%	6.22%
	3	8.57%	9.77%	11.43%	12.27%	11.90%	11.21%	10.05%	8.71%	10.75%	5.34%
	4	7.85%	9.01%	10.50%	12.46%	12.24%	11.55%	11.20%	8.96%	11.29%	4.93%
	5	7.31%	9.29%	9.69%	11.11%	11.72%	10.76%	11.62%	10.64%	12.46%	5.39%
	6	7.27%	8.87%	9.95%	9.84%	11.30%	10.96%	12.03%	11.48%	12.82%	5.48%
	7	7.57%	9.29%	9.18%	9.56%	10.72%	10.98%	11.83%	11.38%	13.74%	5.75%
	8	7.52%	9.69%	9.44%	9.57%	10.50%	9.97%	11.59%	11.68%	14.62%	5.42%
	9	10.05%	10.81%	9.27%	8.41%	8.84%	9.28%	10.49%	11.28%	14.94%	6.63%
	10	15.02%	11.60%	8.55%	7.19%	6.69%	7.84%	9.12%	9.94%	15.73%	8.22%

Note: Value in ij^{th} entry represents the probability that a firm in the i^{th} R&D/Investment decile in year t is in the j^{th} R&D/R&D Capital decile in year t. R&D Capital calculated as $\sum_{\tau=t-5}^{t} (1 - .2 * (t - \tau))\, RD_{\tau}$. Firm-year observation level. Numbers in each row sum to 100% (with possible rounding error).

Table 20: R&D/Investment and Organizational Capital Similarity Matrix

	% of R&D/Inv obs	SG&A Capital/Assets Decile									
		1	2	3	4	5	6	7	8	9	10
R&D/Inv Decile	1	43.24%	15.88%	9.86%	7.01%	6.00%	4.87%	4.24%	3.13%	3.06%	2.73%
	2	20.99%	18.94%	14.06%	11.45%	8.79%	7.13%	5.70%	4.78%	4.13%	4.02%
	3	11.28%	16.66%	14.81%	14.17%	11.40%	9.35%	7.08%	5.99%	5.71%	3.55%
	4	7.46%	13.59%	15.11%	13.85%	13.38%	10.42%	8.74%	7.25%	5.88%	4.33%
	5	5.15%	11.23%	12.17%	13.76%	12.58%	12.21%	10.01%	9.20%	8.30%	5.38%
	6	3.07%	7.47%	10.73%	11.90%	12.85%	12.60%	13.52%	11.71%	9.67%	6.49%
	7	2.63%	5.53%	8.08%	9.49%	11.21%	13.03%	14.41%	14.44%	12.06%	9.12%
	8	1.80%	3.96%	6.50%	8.33%	9.89%	12.28%	13.65%	15.54%	15.49%	12.56%
	9	1.85%	3.18%	4.46%	6.07%	8.07%	10.61%	12.48%	15.83%	18.18%	19.26%
	10	2.22%	3.14%	3.93%	4.09%	6.11%	7.39%	9.92%	12.29%	17.97%	32.94%

Note: Value in ij^{th} entry represents the probability that a firm in the i^{th} R&D/Investment decile in year t is in the j^{th} SG&A Capital/Assets decile in year t. Organizational (SG&A) Capital calculated as $\sum_{\tau=t-5}^{t} (1 - .2 * (t - \tau))\, SGA_{\tau}$. Firm-year observation level. Numbers in each row sum to 100% (with possible rounding error).

Table 21: Doublesorts on Gross Profitability and R&D/Investment

FF3-Alpha		R&D/Investment Quintile				
		1	2	3	4	5
Gross Profitability Quintile	1	-0.696	-0.843	-0.802	0.164	-0.695
		(-2.43)	(-3.14)	(-2.85)	(0.52)	(-2.24)
	2	-0.035	0.022	0.294	0.422	0.326
		(-0.31)	(0.15)	(1.75)	(2.28)	(1.49)
	3	-0.125	-0.087	0.197	0.501	0.581
		(-1.03)	(-0.85)	(2.09)	(4.02)	(3.21)
	4	0.081	-0.073	0.134	0.425	0.437
		(0.67)	(-0.63)	(1.20)	(3.20)	(2.22)
	5	0.259	0.365	0.194	0.067	0.529
		(1.85)	(2.23)	(1.05)	(0.28)	(2.23)

FF5-Alpha		R&D/Investment Quintile				
		1	2	3	4	5
Gross Profitability Quintile	1	0.010	-0.306	-0.419	0.437	-0.512
		(0.04)	(-1.12)	(-1.52)	(1.42)	(-1.65)
	2	0.040	0.426	0.547	0.633	0.612
		(0.35)	(3.07)	(3.09)	(3.19)	(2.87)
	3	-0.162	-0.051	0.215	0.645	0.839
		(-1.28)	(-0.48)	(2.14)	(5.00)	(4.73)
	4	-0.077	-0.134	0.077	0.437	0.698
		(-0.64)	(-1.11)	(0.63)	(3.24)	(3.46)
	5	0.121	0.230	0.267	0.107	0.721
		(0.87)	(1.31)	(1.30)	(0.44)	(2.93)

Note: Firms sorted first into quintiles on Gross Profitability and then on quintiles based on R&D/Investment. Gross Profitability defined as Revenue/Assets. Table reports Fama-French 3-factor and 5-factor value-weighted alphas by group. Alphas are reported as basis points (bps) per month. These results use the same data sample and portfolio construction methodology as the value-weighted results presented in the paper. Numbers in parentheses are Newey-West t-statistics.

Table 22: Doublesorts on Net Profitability and R&D/Investment

FF3-Alpha		R&D/Investment Quintile				
		1	2	3	4	5
Net Profitability Quintile	1	-0.405	-0.171	0.188	-0.525	0.039
		(-1.86)	(-0.72)	(0.80)	(-2.22)	(0.15)
	2	-0.469	-0.180	-0.061	0.033	0.365
		(-3.15)	(-1.12)	(-0.32)	(0.17)	(1.65)
	3	-0.331	-0.010	-0.097	0.107	0.232
		(-2.57)	(-0.08)	(-0.74)	(0.67)	(1.23)
	4	0.096	-0.212	0.104	0.137	0.359
		(0.76)	(-2.30)	(0.86)	(1.24)	(2.44)
	5	0.014	0.092	0.351	0.336	0.588
		(0.12)	(0.85)	(3.27)	(3.32)	(3.88)

FF5-Alpha		R&D/Investment Quintile				
		1	2	3	4	5
Net Profitability Quintile	1	0.038	0.431	0.624	-0.185	0.302
		(0.17)	(1.96)	(2.77)	(-0.74)	(1.19)
	2	-0.368	-0.007	0.170	0.346	0.707
		(-2.38)	(-0.05)	(0.89)	(1.79)	(3.16)
	3	-0.280	-0.074	-0.080	0.301	0.411
		(-2.12)	(-0.54)	(-0.58)	(1.85)	(2.03)
	4	0.094	-0.291	0.071	0.155	0.496
		(0.71)	(-3.11)	(0.58)	(1.37)	(3.22)
	5	-0.145	0.004	0.385	0.287	0.719
		(-1.19)	(0.03)	(3.43)	(2.72)	(4.61)

Note: Firms sorted first into quintiles on Net Profitability and then on quintiles based on R&D/Investment. Net Profitability defined as Net Income/Assets. Table reports Fama-French 3-factor and 5-factor value-weighted alphas by group. Alphas are reported as basis points (bps) per month. These results use the same data sample and portfolio construction methodology as the value-weighted results presented in the paper. Numbers in parentheses are Newey-West t-statistics.

Table 23: Doublesorts on Firm Scaled Investment and R&D/Investment

FF3-Alpha		R&D/Investment Quintile				
		1	2	3	4	5
Scaled Investment Quintile	1	-0.559 (-2.14)	0.259 (1.03)	-0.187 (-0.77)	-1.102 (-3.57)	-0.712 (-1.71)
	2	-0.435 (-2.83)	0.161 (0.78)	0.185 (1.22)	-0.270 (-1.52)	0.091 (0.39)
	3	-0.070 (-0.58)	0.038 (0.31)	-0.025 (-0.21)	0.121 (0.86)	0.343 (2.00)
	4	0.006 (0.05)	-0.077 (-0.83)	0.101 (1.06)	0.477 (3.65)	0.315 (1.76)
	5	0.182 (1.10)	0.255 (2.00)	0.319 (2.04)	0.043 (0.23)	0.771 (3.57)

FF5-Alpha		R&D/Investment Quintile				
		1	2	3	4	5
Scaled Investment Quintile	1	-0.478 (-1.82)	0.130 (0.50)	-0.465 (-1.97)	-1.004 (-2.96)	-0.513 (-1.18)
	2	-0.449 (-2.92)	-0.034 (-0.15)	-0.009 (-0.06)	-0.216 (-1.18)	0.363 (1.40)
	3	-0.136 (-1.06)	-0.039 (-0.29)	-0.048 (-0.39)	0.255 (1.69)	0.518 (2.78)
	4	0.082 (0.76)	-0.037 (-0.39)	0.116 (1.11)	0.596 (4.42)	0.467 (2.57)
	5	0.429 (2.70)	0.381 (2.89)	0.537 (3.49)	0.265 (1.36)	1.040 (4.90)

Note: Firms sorted first into quintiles on Scaled Investment and then on quintiles based on R&D/Investment. Scaled Investment defined as Investment/Assets. Table reports Fama-French 3-factor and 5-factor value-weighted alphas by group. Alphas are reported as basis points (bps) per month. These results use the same data sample and portfolio construction methodology as the value-weighted results presented in the paper. Numbers in parentheses are Newey-West t-statistics.

Table 24: Fama-French 3-factor and QMJ Results

	R&D/Investment Decile											
	0	1	2	3	4	5	6	7	8	9	10	10-1
α	-0.234	0.081	0.027	0.085	0.011	0.201**	0.142	0.329***	0.679***	0.417**	0.973***	0.892***
	(-1.57)	(0.81)	(0.28)	(0.85)	(0.12)	(2.04)	(1.34)	(2.72)	(4.44)	(2.38)	(4.92)	(3.80)
$RMRF$	1.195	0.835	1.065	1.038	1.022	0.974	0.979	1.012	0.954	0.899	0.918	0.083
HML	0.241	0.112	0.154	-0.042	-0.151	-0.331	-0.333	-0.459	-0.669	-0.931	-0.937	-1.049
SMB	0.431	-0.304	-0.158	0.067	-0.017	-0.027	0.066	0.122	0.121	0.413	0.595	0.898
QMJ	0.458	-0.229	0.002	-0.034	-0.062	-0.181	0.130	-0.045	-0.346	-0.528	-0.746	-0.758

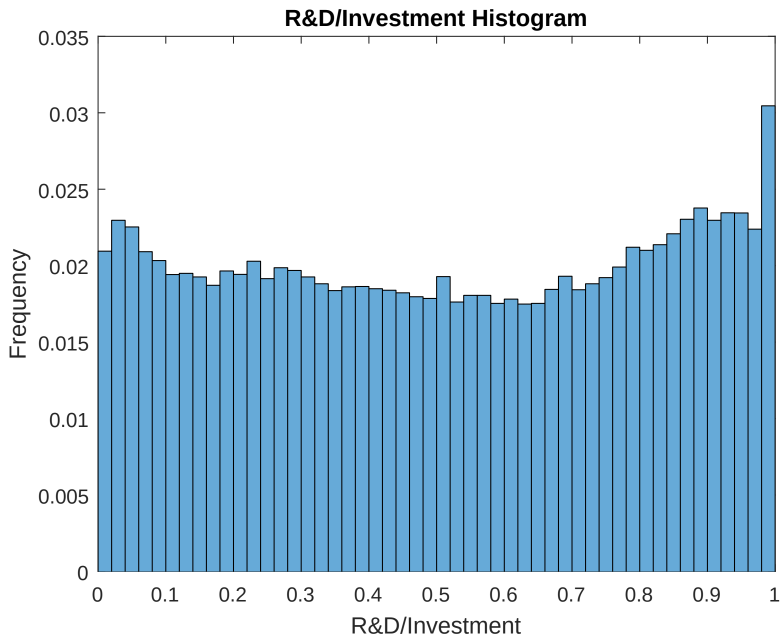
Note: Table reports value-weighted alphas and betas by deciles of R&D/Investment measure after controlling for Fama-French 3 factors and QMJ factor of Asness, Frazzini, and Pedersen (2014). Alphas are reported as basis points (bps) per month. In the top row, *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level. These results use the same data sample and portfolio construction methodology as the value-weighted results presented in the paper. Numbers in parentheses are Newey-West t-statistics.

Table 25: Fama-French 3-factor and Momentum Results

	R&D/Investment Decile											
	0	1	2	3	4	5	6	7	8	9	10	10-1
α	0.065	-0.076	0.021	0.129	0.052	0.150	0.196**	0.281**	0.512***	0.087	0.444**	0.520**
	(0.47)	(-0.79)	(0.24)	(1.43)	(0.59)	(1.56)	(2.11)	(2.41)	(3.50)	(0.53)	(2.38)	(2.41)
$RMRF$	1.081	0.894	1.065	1.032	1.020	1.005	0.953	1.027	1.027	1.027	1.112	0.219
HML	0.145	0.162	0.156	-0.059	-0.167	-0.317	-0.348	-0.443	-0.617	-0.826	-0.766	-0.928
SMB	0.275	-0.226	-0.158	0.078	0.005	0.035	0.022	0.137	0.238	0.592	0.847	1.073
MOM	-0.024	0.020	0.007	-0.069	-0.084	-0.062	0.028	0.022	-0.045	0.012	-0.085	0.064

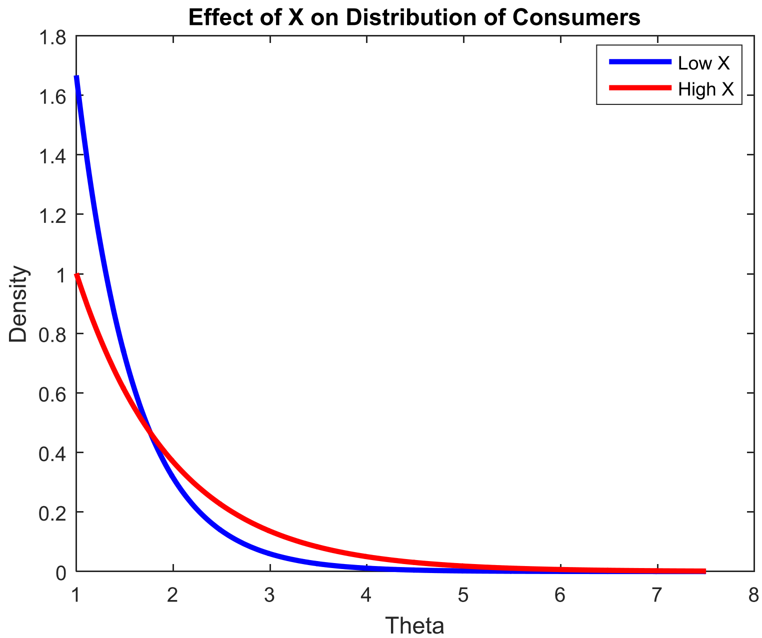
Note: Table reports value-weighted alphas and betas by deciles of R&D/Investment measure after controlling for Fama-French 3 factors and Momentum (based on 2-12 month prior return). Alphas are reported as basis points (bps) per month. In the top row, *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level. These results use the same data sample and portfolio construction methodology as the value-weighted results presented in the paper. Numbers in parentheses are Newey-West t-statistics.

Figure 5: R&D/Investment Distribution



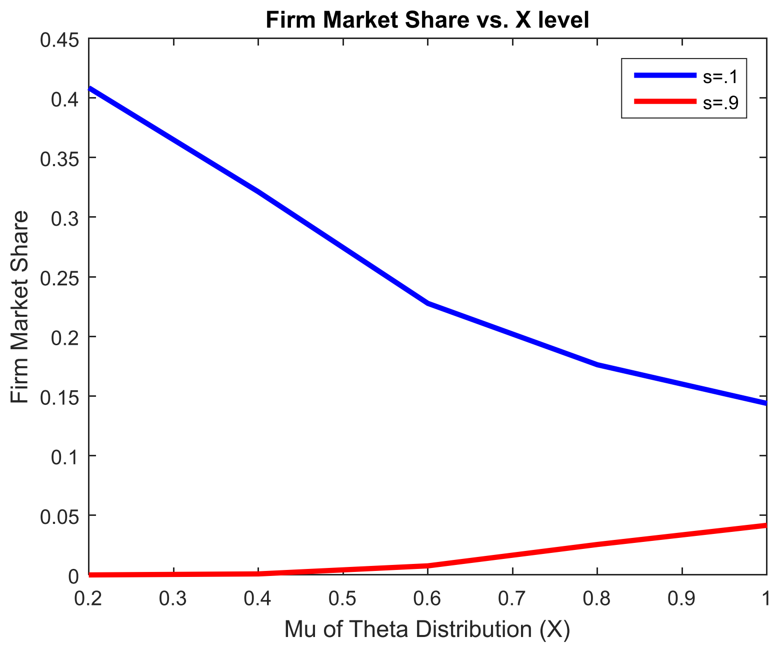
Note: Figure plots the histogram of R&D/Investment firm-year level observations for reported and nonzero values of R&D. Investment is defined as the sum of R&D expenditures and capital expenditures; see Section 2.1 for more details. Approximately 50% of the firm-year observations in the merged sample have missing R&D values, approximately 17% of those with non-missing values have zero values. Firm-year observation level.

Figure 6: Effect of X on Distribution of Consumer Preferences



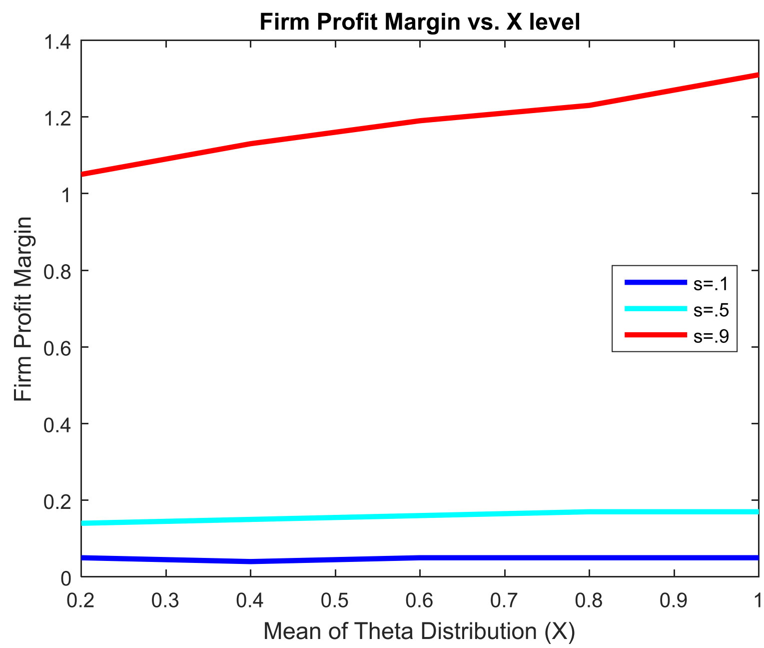
Note: Figure plots the distribution of consumers' theta prefences under two values of the demand state variable X_t. Lower values of X_t (blue line) correspond to distributions which skew towards lower theta values and have fewer high theta values.

Figure 7: Model Market Shares



Note: Figure plots the model-generated market shares of low- and high-quality firms as the preference parameter (X_t) changes. Market shares calculated as the quantity of goods produced and sold by a given firm divided by the quantity produced and sold by all firms. Productivity state fixed to long-run mean.

Figure 8: Model Profit Margins



Note: Figure plots the profit margins of low- , medium-, and high-quality firms as the preference parameter (X_t) changes. Profit margin calculated as the total profit of a firm (revenue less rental costs of capital) divided by the quantity sold. Productivity state fixed to long-run mean.

Appendix B: Proof of Proposition 1

Proposition 1 can be proved by establishing Lemmas 2 and 3.

Lemma 2. *In any pure-strategy Nash Equilibrium, there will be at most one firm producing products of a given quality level* $s_i \forall i$.

Proof. Consider first the problem of a firm seeking to enter that previously did not produce products of any quality level. Since this firm is switching quality levels (in the sense that it previously had no quality level and is now entering a quality level) it must pay some switching costs, denoted by c (without loss of generality, assume that this cost is the same for firms switching from no previous quality level as it is for firms switching from a different previous quality level.) If this firm enters a quality level s_j where there is an existing firm producing, then both this new entrant and the existing firm will decide to produce the same quantity of products, because these firms are identical. Given that these identical firms are competing for the production of a homogeneous good, they will compete on the prices they set such that both firms earn zero profits in equilibrium. Therefore, the payoff to the entrant from entering any quality level which has an existing firm will be $-c < 0$. Since this is less than the payoff for not entering at all (0), this new entrant will never choose to enter a quality level which has an existing firm.

The comparison for a firm which is producing products of a different quality level s_i is even starker. By not switching quality levels, this firm earns profits π_i, which are always weakly positive since the firm can choose to produce zero units of goods and rent zero units of capital and thus earn zero profits. The analysis for the profits of the firm if it enters a quality level where there is already an existing firm is the same as above, and this firm will earn $-c < 0$. Since $-c < 0 \leq \pi_i$, this firm is always strictly better off by not switching to a quality level where there is an existing firm producing goods.

Therefore, no firm will enter or switch into a quality level where it believes that there will be another firm. Since these beliefs are correct in equilibrium, in any pure-strategy Nash Equilibrium, firms will have perfect knowledge of the quality levels occupied by every other firm and will not choose to produce products in any of these occupied quality levels. Thus, in any pure-strategy Nash Equilibrium, there will never be more than one firm producing products of any given quality level.

□

Lemma 3. *Among all possible Nash Equilibria, the initial allocation where firm j produces quality level s_j is Pareto-optimal.*

Proof. In any pure-strategy Nash Equilibrium, there will always be exactly one firm per quality level. This is because each quality level is initially occupied by one firm, and this firm earns (weakly) positive profits in every period. As a result, each of these firms has no incentive to exit, and so will always remain in the economy. Then, as long as there are at least N firms in the economy (the initial number) and N different quality levels, if there is no more than one firm producing products of a given quality then each quality level will have no fewer than one firm, by the Pigeonhole Principle. Combining this with Lemma 2, each quality level will have exactly one firm in a pure-strategy Nash Equilibrium.

As a result, any pure strategy Nash Equilibrium consists of an assignment of N firms to N quality levels such that each quality level has exactly one firm. The initial allocation of firms such that firm j produces quality level s_j is one such equilibrium. This equilibrium can be shown to be Pareto optimal as follows. In this equilibrium, the N firms earn profit levels $\pi_1, \pi_2, \ldots, \pi_i, \pi_j, \ldots, \pi_N$. Any pure strategy modification would result in the switching of two profit levels, and the deduction of c from each. If one profit level is higher than the other, then the firm which moves from the higher to the lower profit level will necessarily be worse off. If the two profit levels are equal, then the switch results in both firms paying switching costs and both being worse off as their profits have been reduced by c. Thus there exist no pure-strategy modifications to the initial allocation of firms that make one firm better without making one firm worse off. Note that this is not necessarily the case with other equilibria because if those equilibria involve the switching of firms, then reducing those switching costs can potentially make multiple firms better off without harming other firms. For example, if $\pi_i = \pi_j$ and the Nash Equilibrium involved firms i and j switching quality levels, then a Pareto improvement on this would be for firm i to stay at quality level s_i and firm j to stay at quality level s_j.

There also exist mixed-strategy Nash Equilibria where some firms have probabilities of occupying various quality levels. Note that none of these equilibria represent a Pareto improvement over the initial allocation either. This can be seen in many ways, but one way is to examine the aggregate profit. The aggregate profit under any mixed-strategy Nash Equilibrium will be weakly lower than that under the initial allocation. This is explained by several components. First, since firms make identical quantity decisions once they are put into a given quality level, if there are quality levels with only one firm under the mixed-strategy Nash Equilibrium, then the firms in those quality levels will earn the same profits as the firms in those quality levels under the initial allocation, less any switching costs. Therefore the profits of these firms will be weakly lower. Second, if there are quality levels with multiple firms, the firms in those quality levels will earn zero profits, again weakly lower than under the initial allocation. If the mixed-strategy Nash Equilibrium involves any switching at all–that is, if there are any firms that use mixed strategies–then the aggregate profits will be strictly lower. In such a mixed-strategy Nash Equilibrium, these lower profits can be split among a greater, lower, or equal number of firms. If the lower profits are split among a greater or equal number of firms, then it is clear that some firms must be worse under this equilibrium than in the initial allocation. If they are split among fewer firms, then there are some firms that would earn positive profits under the initial allocation (since all firms under the initial allocation earn strictly positive profits) who now earn zero profits.

$\square$