Innovation Awards, Product Segmentation, and Stock Returns

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Abstract: This paper connects technological innovation to product market segmentation using a prestigious award for technology breakthroughs in product inventions: the R&D 100 Award. We argue that award-winning outcomes have asset pricing implications because awarded firms have the growth opportunities to promote their products to high-end markets, which increases revenue procyclical to aggregate consumption and results in higher systematic risks. We find that, compared with their matched industry counterparts, awarded firms are associated with lower product similarity, lower product fluidity, and higher profitability over the future five years. Moreover, these firms outperform their comparable peers by 3% in annual returns and have both significantly higher procyclicality of sales growth and market betas. Moreover, the award-return relation is more pronounced in periods of higher aggregate consumption growth and among firms with higher R&D investments.

Keywords: Innovative Product Award, Product Segmentation, Procyclicality, Consumption Risks, Growth Opportunities, Stock Returns

JEL classification: E23, G12, L22, O31

1 Introduction

Innovative product awards are specific titles or marks of recognition granted to products and their producers in honor of their novelty, originality, and creativity in particular technology fields. These awards, especially prestigious ones, serve as important indicators of quality and merits (in various dimensions) of firms and products, and are highly recognized by industry professionals and technology communities. Thus, innovative product awards likely attract market attention, enhance company image, and help firms differentiate their products from competitors. Award-winning firms consider prestigious awards to be cornerstones of company reputation and list them on their respective firms' webpages to highlight such achievements and legacies.[1] However, to the best of our knowledge, the asset pricing implications of such awards are underexplored in the finance literature and, thus, deserve further investigation.

In this paper, we focus on the R&D 100 Award, which has been granted by *R&D Magazine* since 1965 to honor great R&D pioneers and their innovative products in all industries. Over the past five decades, *R&D Magazine* has announced the application process to the public in either spring or summer, and formed panels of judges to select and grant awards to the 100 most technologically significant new products and services that had been commercialized in the market since the previous year.[2] For its prestige of high standard and long history, the R&D 100 Award is often nicknamed the "Oscar of Innovation."[3] The winners of the R&D 100 Award are generally announced at the end of fall or winter. When a product is finally rewarded with the prize, the producer is entitled to use the term "R&D 100 Award" and its accompanying logo to market and

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[1] For example, Goodyear and United Technologies list their awards on the webpages of company history (https://corporate.goodyear.com/en-US/about/history.html and http://www.utrc.utc.com/our-history.html). 3M lists its awards on the webpage that provides its company profile and awards (http://solutions.3m.com/wps/portal/3M/en_US/3M-Company/Information/Profile/Awards/).

[2] There is no further ranking within the 100 winning products and services. Applicants can be companies, individuals, or non-profit institutes, such as universities and national laboratories. Panels of judges consist of outside experts with experience in the areas they are judging, such as professional consultants, university faculty members, and industrial researchers. Judges must also be unbiased and possess no conflicts of interest with any entries that they may judge.

[3] The term "Oscar of Innovation" is also used by many award-winning firms and organizations, including NASA (https://technology.grc.nasa.gov/featurestory/rd100-press-release), Mercedes-Benz (http://mercedesblog.com/mercedes-benznanoslide-technology/), Toyota (https://www.toyota.com/usa/environmentreport2014/carbon.html), and the Los Alamos National Lab (http://www.lanl.gov/discover/news-release-archive/2016/November/11.15-rd-100-awards.php).

promote the product. The award thus offers recipient firms a chance to signal the novelty of their award-winning products,[4] to differentiate their products from competitors, and to target high-end customers. We use two prominent examples, the HP Jet Fusion 3D 4200 Printing Solution and the Intel Core processor, to illustrate this argument.

As one of the most recent awardees in 2017, the HP Jet Fusion 3D 4200 Printing Solution is regarded as ideal for prototyping and short-run but high-value-adding manufacturing needs, with high productivity to meet same-business-day demands at the lowest cost per part. For example, experiment data shows that this product provides access to agents and materials with costs up to 40% lower.[5] As Ramon Pastor, vice president and general manager of HP Multi Jet Fusion, stated, "this award recognition differentiates HP and reinforces our position as a catalyst in 3D printing and an extensive heritage of printing leadership."[6]

From 1994 to 2010, the Central Processing Unit (CPU) market was dominated by Intel, with Pentium aiming for mid-to-high-end markets and Celeron aiming for low-end markets. However, the demands of the high-end computation-efficient markets, driven by work stations and advanced electric game players, were expanding rapidly yet remained unfilled. In 2011, R&D Magazine announced the Intel Core processor as a recipient of its R&D 100 Award. In the same year, Intel targeted its Core processor to the mid-to-high end market, moving Pentium to the entry-level market and bumping Celeron to the low-end market.[7] Intel treated the reception of its R&D 100 Award as a key determinant of its successful marketing of new high-end products, as it listed this accomplishment on its website and also publicized its case on the R&D 100 Award website as a successful example that connected this award to product commercialization.

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[4] Recent studies have started to use the R&D 100 Award to measure firms' technological breakthroughs (e.g., Narin et al. (1987), Verhoeven et al. (2016), and Chen et al. (2017)).

[5] The function and reasons of the award-winning HP Jet Fusion 3D 4200 Printing Solution are described on the webpage of the 2017 R&D 100 Award (https://www.rd100conference.com/awards/winners-finalists/6747/hp-jet-fusion-3d-4200-printing-solution/).

[6] Source: HP's newsroom webpage (https://developers.hp.com/hp-3d-printing/news/hp-jet-fusion-3d-printing-wins-innovation-year).

[7] The winning announcement of the 2010 Intel Core processor family was unveiled on the webpage of the R&D 100 in 2011 (https://www.rd100conference.com/awards/winners-finalists/926/next-generation-processors-enhance-graphics-speed/), and Intel also advertised its winning award on the webpage of its company newsroom (https://newsroom.intel.com/chip-shots/chip-shot-intel-core-snags-rd-100-award/).

Winning the award enables awarded firms to market their products to high-end customers, and may thus have asset pricing implications. As award-winning firms are more likely to commercialize the high-end markets, these firms gain access to riskier growth opportunities, and such a market position likely increases winner firms' profitability and risks. To formalize this intuition and motivate empirical analyses, we build a two-product model in the Online Appendix. Observing the fact that high-end goods (e.g., 3D printers and upgraded CPUs) are produced to meet advanced demands, we expect that high-end consumption is higher when the economy performs better, but it is lower when the economic conditions are worse. Therefore, the sales of high-end goods are more procyclical than those of low-end goods.

We propose the following four testable hypotheses. First, under the notion that the sales and profits in high-end markets are more procyclical to aggregate consumption, and thereby riskier, than those in low-end markets, awarded firms with growth opportunities in riskier, high-end markets may demand higher expected stock returns (Hypothesis 1). Due to their excessive procyclicality of sales growth in high-end markets, awarded firms have higher systematic risk exposure (Hypothesis 2).

Consumption risks are expected to be higher when the current consumption growth is higher.[8] Therefore, awarded firms with excessive exposure to consumption risks may demand a higher risk premium in periods of higher consumption growth. In other words, the award-return relation may correlate with aggregate consumption growth (Hypothesis 3). Finally, as a firm's R&D investment increases with its number of growth opportunities, the award, once realized, will capitalize more growth opportunities and bring higher additional systematic risks to an awarded firm with higher ex-ante R&D investment. Therefore, the risk premium of awarded firms is higher among R&D-intensive firms (Hypothesis 4).[9]

To examine these asset pricing implications, we collect total 5,144 award records

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[8] When the aggregate consumption follows a logarithm drifted random walk (Hansen and Singleton, 1983; Chapman, 1998) or a logarithm AR(1) process (Campbell and Cochrane, 1999), the volatility of consumption will be higher if the current consumption growth rate is higher.

[9] The positive relation between R&D investment and number of growth opportunities is endogenized in our model in the Online Appendix and supported by prior studies, including Lev and Sougiannis (1996), Berk et al. (1999), Chan et al. (2001), Carlson et al. (2004), Aguerrevere (2009), Li (2011), Abel and Eberly (2011), Garleanu et al. (2012), Lin (2012), and Ai and Kiku (2013), among others.

that were granted to U.S. public firms in the sample period from 1965 to 2014: these awards were granted to 601 unique firms.[10] Considering the rarity of the awards and their long-term impact on firm performance, we define a firm as an award-winner if it receives at least one award over the past five years. Since a firm that is able to make award-winning breakthroughs may be quite different from most of the other firms, we follow the methodology of Daniel et al. (1997) and construct a comparable benchmark to each awarded firm. Specifically, we identify an unawarded firm as a comparable benchmark to the awarded firm if it falls in the same quintile of market capitalization, in the same quintile of book-to-market ratio, in the same quintile of momentum, and in the same 12-industry classification by Fama and French (1995) by the same year end. To ensure that an awarded firm and its unawarded benchmark firm are comparable in ex-ante growth opportunities, we also restrict the unawarded firm to be within the range of [-1%, +1%] with respect to the awarded firm's R&D over total assets ratio.

The first set of our empirical tests provides evidence consistent with our intuition that award-winning firms receive growth opportunities in segmented high-end markets. We document that, measured by the product similarity score (Hoberg and Phillips, 2016) and the product fluidity score (Hoberg et al., 2014), awarded firms, when compared with their unawarded counterparts, are associated with greater market differentiation and lower product threats over the next five-year horizon. Furthermore, we find that, when compared with their benchmarked counterparts, firms that win awards generate higher returns on equity (ROE) over the next five-year horizon.

We implement portfolio sorting to examine the award-return relation and find supportive evidence for Hypothesis 1. We form an awarded portfolio that takes equal positions in all awarded firms that win at least one award from year *t*−4 to year *t*, and hold this portfolio from July of year *t*+1 and June of year *t*+2.[11] We also form an unawarded portfolio that takes equal positions in all benchmarked unawarded firms,

[10] The average probability for a public firm to win one or more awards in a year is 0.6%. Award data can be downloaded via https://www.rd100conference.com/awards.

[11] We use equal-weighted stock returns for three reasons: first, we only have 31 awarded firms on average per year; and second, the awarded firms and the unawarded benchmarked firms are constructed to be highly comparable in firm size. Third, as shown in Block and Keller (2009), this award is not dominated by large public firms over the past few decades.

and hold this portfolio for the same period. Lastly, we construct an awarded-minus-unawarded (AMU) portfolio by going long in the awarded portfolio and going short in the unawarded portfolio and hold it for the same period. The average monthly returns and alphas from the AMU portfolio range from 0.21% to 0.32% under different factor models. Further analyses imply that such outperformance in stock returns is persistent up to five years once firms are awarded, which confirms our risk-based explanation of the award-return relation (Chambers et al., 2002).

We find further supportive evidence for Hypothesis 2 with respect to procyclicality and systematic risk exposure. Results from pooled regressions imply that, if an unawarded firm counter-factually becomes awarded, then its future five-year procyclicality of sales growth with respect to aggregate consumption growth will increase by 0.03-0.07 (the sample average of unawarded firms is 0.26), and its future five-year market beta will increase by 0.08-0.13 (the sample average of unawarded firms is 1.06); all estimates are significant. It is robust when we control for the dependent variable estimated from the previous five years, as well as control for R&D expenditures, SG&A expenses, advertisement expenses, and year and industry fixed effects.

Consistent with Hypothesis 3, we find that this risk premium is procyclical to aggregative consumption. Specifically, if the aggregate consumption growth increases by one standard deviation (i.e., 13.21%), then the monthly return on the AMU portfolio will increase by 0.26% or almost double from the average AMU return (i.e., 0.28%). Finally, we document that the risk premium of awarded firms differs in subgroups of R&D investments. Using two-way sequential portfolio sorting, we find that the monthly returns and alphas of the AMU portfolio in the high R&D group range from 0.75% to 1.30% and are statistically significant, while those in the low R&D group range from -0.11% to 0.09% and are insignificant. Such evidence supports Hypothesis 4, which connects the risk premium of awarded firms with growth opportunities.

Although we have presented the award-return relation by matching awarded stocks with unawarded stocks along several important dimensions common in the asset pricing literature, one may still be concerned that such return predictive ability is spurious and due to ex-ante omitted characteristics rather than the award outcomes, such as better reputation, more resources, and superior innovating and producing skills. We argue that, if our main result is driven by such persistent omitted variables, then both award-winning outcomes and stock-return outperformance should concur. Our empirical results based on a falsification test go against the omitted-variable explanation. Specifically, when we define a firm as *pseudo*-awarded by year t if it receives at least one award in the future five years (from year t+1 to year t+5) and a firm as *pseudo*-unawarded by year t if it is comparable with the *pseudo*-awarded firm but does not receive any award in the same period, the return difference between *pseudo*-awarded stocks and *pseudo*-unawarded stocks from July of year t+1 to June of year t+2 becomes insignificant in all model specifications and even negative in some factor models.

Overall, we propose and present empirical evidence for the effect of product market segmentation on financial valuation. This study is related to Ait-Sahalia et al. (2004), which use the import data of 70 French manufacturers of luxury goods to identify luxury consumption and successfully explain the equity premium puzzle. Departing from their focus on households' luxury consumption and associated risk, we focus on firms' innovative award-winning events to measure their access to high-end markets. Our argument based on market segmentation is also related to prior studies on the asset pricing implication of brand names and advertising activities (Vitorino, 2013; Belo et al., 2014). Our focus on technology novelty of product invention may explain why firms are willing to invest in brand capital and why such investment leads to return predictability.

Our study also provides new evidence to the growing literature on the relation between technological innovation and asset pricing. Although numerous studies have investigated the relation between asset prices and the dynamics of technological innovation (e.g., patents, general-purposed technologies, or investment-specific technologies),[12] very few have examined new products as the commercialization of

[12] These studies measure technological innovation by patents, general-purposed technologies, or investment-specific technologies: see Pakes (1985), Greenwood et al. (2001), Deng et al. (1999), Hobijn and Jovanovic (2001), Bloom and Reenen (2002), Laitner and Stolyarov (2003), Kogan (2004), Hsu (2009), Pastor and Veronesi (2009), Papanikolaou (2011), Kogan and Papanikolaou (2014), Kogan et al. (2017), and Zhou (2017), among others.

innovative technologies. Our paper thus fills this gap in the literature by highlighting the asset pricing implications of innovative product awards.

The rest of the paper is organized as follows. In Section 2, we compare the future product market performance between awarded and unawarded firms. We test our hypotheses in Section 3. Section 4 concludes.

2 R&D 100 Awards, Product Segmentation, and Profitability

2.1 Data and summary statistics

In this section, we investigate the relation between a firm's receipt of the R&D 100 Award and its future product market performance. To do so, we manually collect the full list of products receiving the "R&D 100 Award" published by *R&D Magazine* from 1965 to 2014. We further match these products to their developers as U.S. public companies if these firms are listed as the developers or co-developers of the awarded products. For example, in 2014, the 100 awarded products were co-developed by 88 unique firms and 30 unique public firms. From our full sample from 1965 to 2014, we end up with 5,144 awards granted to 601 unique U.S. public firms.

In Figure 1 Panel A , we illustrate the distribution of award outcomes across the Fama-French 12 industries (Fama and French, 1995). The four industries winning the most R&D 100 awards in our sample are Durables (8%), Manufacturing (31%), Chemicals, (12%), and Business Equipment (31%). In Panel B, we present the time series of awards in these industries and find that the award outcomes vary significantly over time.

[Figure 1 here.]

Since we argue that an awarded product, although rare, may grant a firm access to high-end markets and therefore generate more risky and procyclical sales in the long-term future, we identify a firm as awarded by year *t* if it receives at least one award in the previous five years (from year *t*-4 to year *t*).[13] In an average sample year, 118 firms

[13] It is also a common practice to roll windows through the sample over a five-year horizon; this practice is widely used in prior studies, such as McGahan and Silverman (2001) and Hirshleifer et al. (2013).

are defined as awarded.

To compare the performance of awarded firms with that of unawarded firms, we first adopt the characteristic-based sorting method originally proposed by Daniel et al. (1997). Specifically, we identify an unawarded firm in year t as a comparable benchmark to an awarded firm if it does not win any award in the previous five years from year t-4 to t but falls in the same quintile of market capitalization, in the same quintile of book-to-market ratio, in the same quintile of momentum, and in the same 12-industry classification according to Fama and French (1995) by the end of year t. To ensure that the awarded firms and their unawarded benchmarks are comparable in ex-ante growth opportunities, we also restrict the two groups to be within the range of [-1%, +1%] with respect to their R&D over total assets ratios in year t. When we perform the matching method, we exclude from our sample any awarded firm that fails to find a comparable unawarded firm. Finally, we extract the stock transaction data from the Center for Research in Security Prices (CRSP) database and the accounting data from the Compustat database.

In Table 1 Panel A, we show that, in an average year, we identify 31 matched awarded firms and 49 benchmarked unawarded firms.[14] The sample period is 1969-2014 because the award data is collected from 1965 and our sample of awarded firms is based on a rolling five-year window. The ratio of awarded firms over benchmarked unawarded firms by industry is around 0.94 with a standard deviation of 0.63. In Panel B, we compare the mean characteristics of the unawarded group with those of the awarded group;[15] these characteristics include market capitalization ($4,454 billion vs. $7,373 billion), book-to-market ratio (0.73 vs. 0.75), momentum (18.71% vs. 15.12%), total assets ($4.32 billion vs. $8.94 billion), the ratio of R&D expenditure over total asset (5% vs. 5%), the ratio of capital expenditures over total assets (6% vs. 6%), the ratio of costs of selling, general, and administration (SG&A) over total assets (26% vs. 25%), the ratio of advertising expenses over total assets (4% vs. 3%), return on equity

[14] The mean, median, and standard deviation of the number of awards received in the previous five-year window by each firm-year observation for the matched awarded firms are 2.05, 1.00, and 2.66, respectively.

[15] To mitigate any bias due to extreme industry-year observations, we compute the mean characteristics by first averaging within each industry-year, then averaging across all sample years, and finally averaging across all industries.

(ROE) as defined as the ratio of net profit over the market value of equity (4% vs. 4%), and the ratio of net sales over total assets (107% vs. 104%).[16]

[Table 1 here.]

2.2 Future product market performance and award outcomes

We then examine whether the awarded firms will have more high-end products in the future when compared with their unawarded counterparts. We first consider the total similarity score proposed by Hoberg and Phillips (2016) as a proxy for product market segmentation that a firm faces in a certain year. To construct the total similarity score to measure how similar a focal firm's products are with its key rivals', Hoberg and Phillips (2016) first compute a matrix of pairwise similarity scores between firms based on the textual analysis of product descriptions disclosed in their 10-K announcements and then calculate the total similarity score in a firm-year, which is computed as the sum of the pairwise similarities between the focal firm and top 2 percent peers that have the largest pairwise similarity scores in the given year. As we argue that awarded firms receive growth opportunities in high-end markets and the capacity to differentiate themselves from their unawarded counterparts, we expect that their future products are more differentiated; as a result, their total similarity score is lower.

To test such hypothesis, Table 2 Panel A1 first uses paired-sample *t*-test to compare the difference of the total similarity score averaged across year t+1 to t+5 between awarded firms and their unawarded benchmarks. Our results imply that the future five-year averaged product similarity score of the awarded firms is 0.89 or 26% (=0.89/3.47) lower than that of the unawarded counterparts. Such difference is statistically significant at the 1% level.

[Table 2 here.]

Table 2 Panel A2 then regresses the total similarity score averaged across year t+1 to t+5 as a dependent variable on a dummy indicating whether the firm is awarded at

[16] In an unreported test, we find that these indicators exhibit skewed distributions; the median, in this situation, delivers more comparable values than the mean, as it is less influenced by outliers.

year *t* (defined as winning at least one award from year *t*-4 to *t*) or not. In addition to year fixed effects and industry fixed effects, we control for the following variables in year *t* to mitigate any bias caused by the ex-ante heterogeneity in firm characteristics: market capitalization (*ln(Size)*), book-to-market ratio (*ln(B/M)*), and stock price momentum (*MOM*). Furthermore, we include R&D expenses at year *t* to control for the ex-ante heterogeneity in growth opportunities and include SG&A expenses and advertisement expenses to control for inputs in product-market development. More importantly, we include the product similarity score at year *t* (*Current Total Similarity*) as one of the independent variables in our panel regressions to control for persistence in dependent variables, so we may mitigate the reverse causality issue.

As presented in Table 2 Panel A2, our results confirm that the difference in future product similarity between the awarded firms and the benchmarked unawarded firms is not driven by other firm characteristics. For instance, when we include all firm characteristics and all fixed effects in column (8), the coefficient is -0.18 with a statistical significance at the 1% level.

Since high-end markets are expected to have higher barriers to entry, awarded firms may face fewer product threats. To test such a negative relation between award outcomes and product threats, we measure the product threats that a firm is facing with its product fluidity score, as proposed by Hoberg et al. (2014). Technically, the product fluidity in a firm-year is a cosine similarity between a vector indicating words used by the focal firm in its 10-K in the current year and a vector indicating the change in the use of these words by other firms from the previous year to the current year; therefore, this fluidity intuitively captures how rivals change product words that overlap with the focal firm's vocabulary. Following the argument in Hoberg et al. (2014), a fluidity score, then, is a valid proxy for product threats, as it focuses on product space dynamics and changes in products.

To test the negative relation between award outcomes and product threats, Table 2 Panel B1 first uses paired-sample *t*-tests to compare the difference of the product fluidity score averaged across year *t*+1 to *t*+5 between awarded firms and their unawarded benchmarks. Our results suggest that the future five-year averaged product fluidity score of the awarded firms is 0.20, or 5% (=0.20/3.99) lower than that of their unawarded counterparts. Such difference is statistically significant at the 10% level.

Table 2 Panel B2 further runs panel regressions of the product fluidity score averaged across year *t*+1 to *t*+5 as a dependent variable on a dummy indicating whether the firm is awarded at year *t* (defined as winning at least one award from year *t*-4 to *t*) or not. The fluidity score at year *t* and other control variables as used in Panel A are included in regressions. Our results confirm that the awarded firms are associated with lower product threats in the future five years than their unawarded benchmarks by 0.02-0.06. These coefficients are all statistically significant at the 5% level or better.

The higher product differentiation and lower product threats could lead to higher profitability. Using ROE as a proxy of profitability, we use paired-sample *t*-tests in Table 2 Panel C1 and show that the future five-year average ROE of the awarded firms is 200% (=0.02/0.01) higher than that of the unawarded matched firms; such difference is statistically significant at the 1% level. Also, our panel regressions in Table 2 Panel C2 confirm that the outperformance of awarded firms in profitability is not driven by firm and industry characteristics. In sum, Table 2 supports our argument that awarded firms have more access to high-end markets, create greater market differentiation, and face lower product threats, and subsequently perform better in profitability than their benchmarked unawarded counterparts.

3 R&D 100 Awards and Asset Pricing Implications

In the previous section, we empirically document the positive impact of the R&D 100 Award on future product segmentation and profits. Based on these results supporting the award-winners' better access to high-end markets, we propose four testable hypotheses about the asset pricing implications of award outcomes: awarded firms have higher expected stock returns than unawarded firms (Hypothesis 1), the procyclicality and systematic risk exposure of awarded firms is higher than that of unawarded firms (Hypothesis 2), the award-return relation is procyclical to aggregate consumption growth (Hypothesis 3), and the award-return relation is more pronounced for firms with higher R&D investments (Hypothesis 4). In this section, we implement direct empirical tests to examine these hypotheses.

3.1 Future stock returns and award outcomes

To test the positive award-return relation of Hypothesis 1, we first examine whether the award outcomes lead to positive and significant abnormal returns when adjusted for exposures to risk factors. Specifically, we construct an equal-weighted awarded portfolio at June of year t+1 by including all listed firms awarded at least once in the previous five years from year t-4 to t, and then track the excess return (i.e., stock return in excess of the one-month Treasury bill rate) on this portfolio from July of year t+1 to June of year t+2. The sample of awarded firms starts in 1969 and ends in 2014 because we use a rolling five-year window of award records to define awarded firms, and the award data is collected from 1965. Thus, we track the monthly returns on the awarded portfolio from July of 1970 to June of 2016.

To adjust for well-documented systematic risks, we further regress the monthly excess return on a wide range of risk factors to estimate alphas (i.e., the coefficient on the intercept term) in different models. The risk factors that we consider include the market factor (MKT) in the capital asset pricing model (CAPM), the size factor (SMB) and the value factor (HML) in the three-factor model (FF3) of Fama and French (1993), the momentum factor (UMD) in the four-factor model (FF4) of Carhart (1997), and the profitability factor (RMW) and the investment factor (CMA) in the five-factor model (FF5) of Fama and French (2015) and Fama and French (2017). Moreover, we also include the R&D factor (XRDF) following Chan et al. (2001), which reflects the risk premium associated with R&D investments.[17]

In Table 3, we report the average monthly excess returns and alphas. We find that the abnormal return of the awarded portfolio is positive and significant at the 1% or 5% level in all factor models, except for Column (8). For instance, when we control for the

[17] The R&D factor is the return spread between the top and bottom quintile portfolios sorted by R&D capital ratio, which is the accumulative R&D expenses in the past five years at a 20% obsolescence rate scaled by market equity.

Fama-French six factors (FF5 plus UMD) in Column (9), the monthly abnormal return is 0.29% and significant at the 1% level. Controlling for the exposure to risks associated with R&D investment lowers the abnormal returns by only a small amount. For example, when we control for the R&D factor in addition to the Fama-French six factors, the monthly abnormal return is 0.22% and still significant at the 1% level as shown in Column (10). Drawing from these results, we find that the awarded firms have positive and statistically significant abnormal returns, and these abnormal returns cannot be explained by the well-documented risk factors.

[Table 3 here.]

We then conduct portfolio sorting analysis to directly test our first hypothesis that firms recognized by innovative product awards outperform their unawarded peers in stock returns (Hypothesis 1). To do so, at the end of year *t* from 1969 to 2014, we use the same methodology elaborated in Section 2 and identify the comparable unawarded firms of each awarded firm of highly similar size, book-to-market ratio, momentum, and R&D over total asset ratio, and in the same FF12 industry. Any awarded firm for which we fail to find comparable unawarded firms is excluded from our sample. We form an awarded portfolio that takes equal positions[18] in all awarded firms that win at least one award from year $t-4$ to year t, and hold this portfolio from July of year $t+1$ and June of year $t+2$. We also form an unawarded portfolio that takes equal positions in all benchmarked unawarded firms, and hold this portfolio from July of year $t+1$ and June of year $t+2$. To compare the difference in expected stock returns of awarded firms and their benchmarked unawarded firms, we construct an awarded-minus-unawarded (AMU) portfolio by going long in the awarded portfolio and going short in the benchmarked unawarded portfolio, and then hold this portfolio over the next twelve months from July of year $t+1$ and June of year $t+2$.[19]

Table 4 shows that the average monthly AMU spread is 0.28%, which is

[18] We use equal-weighted stock returns because there are 31 awarded firms on average; second, the awarded firms and the benchmarked unawarded firms are constructed to be highly comparable in firm size; and third, as shown in Block and Keller (2009), this award is not dominated by large public firms over the past few decades.

[19] We use a six-month lag to form portfolios in order to make our results comparable to prior studies, such as Fama and French (1993) and Fama and French (2015).

statistically significant at the 5% level.[20] Although our awarded firms and benchmarked unawarded firms are matched in the same industry and with similar size, book-to-market ratio, momentum, and R&D intensity, we also try to control for their exposure to several risk factors embedded in factor models, including the market factor (MKT), the size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW), the investment factor (CMA), and the R&D factor (XRDF). When we control for these risk factors, our results do not alter the magnitude of the awarded-minus-unawarded spread much. For example, when we adjust for systematic risk exposures in the Fama-French six-factor model (FF6) in Column (9), our monthly return on the AMU portfolio is 0.26% and remains statistically significant at the 5% level. Controlling for the R&D factor yields a slightly smaller alpha (i.e., 0.23%) but remains statistically significant at the 10% level, as shown in Column (10). The results of Fama-MacBeth regressions are highly consistent with our portfolio analyses, and we report these results in our Online Appendix Table OA2.

[Table 4 here.]

In Figure 2, we illustrate the time-series variation of the performance of our long-short strategy based on award outcomes during our sample period from July of 1970 to June of 2016.[21] Aside from significant shoot-ups that occurred in years 2000 and 2007, the performance of our strategy is quite stable over different time periods. Moreover, our long-short strategy does not experience large draw-backs during crisis periods, such as years 1987 and 2008; in fact, the cumulative return of the AMU portfolio reached its peak at 450% around year 2007. We also compute the abnormal return based on the Fama-French three-factor model of our long-short strategy. Specifically, we first run a full-sample regression of the monthly return on the AMU portfolio on the market factor, the size factor, and the value factor, and then calculate the abnormal return in each month by the monthly portfolio return minus the product of coefficient estimates and monthly risk factors. We also plot the cumulative abnormal return of the AMU portfolio

[20] We report the alphas and factor loadings in all of our factor models for both the awarded and unawarded portfolios in our Online Appendix Table OA1.

[21] Since the award data is available from 1965 and we construct the AMU portfolio based on a rolling five-year window of award records, the return on the AMU portfolio is available since 1970.

in Figure 2, and this plot displays a similar pattern, peaking at 600% in 2007.

[Figure 2 here.]

We further explore the long-term performance of our AMU portfolio up to a five-year horizon. Examining the long-term performance helps us justify a risk explanation for our earlier results because mispricing-based return predictability should not last for many years (Chambers et al., 2002). Specifically, we trace the cumulative returns of investments in both the awarded portfolio and the benchmarked unawarded portfolio from July of year *t*+1 (the 1st month since the portfolio is formed) to June of year *t*+6 (the 60th and last portfolio month). As we show in Figure 3, the curves illustrating the cumulative returns of both the awarded portfolio and the benchmarked unawarded portfolio are upward sloping during the 60-month window post portfolio formation. Further comparison implies that the performance of the awarded portfolio is persistently superior to that of the benchmarked unawarded portfolio: the cumulative return of the long-short strategy experiences a consistent upsurge and peaks at 230% during the 60 months. This long-lasting outperformance of the awarded portfolio supports our hypothesis that the awarded firms are exposed to higher long-term systematic risks.

[Figure 3 here.]

Although we have claimed the robustness of the outperformance of the awarded stocks by matching them with unawarded stocks along several important dimensions in the asset pricing literature, one may still be concerned that such outperformance is due to omitted variables rather than the award outcomes. For instance, one may argue that the award-winning firms are the firms, ex ante, with better reputation, more sources, and superior innovating and producing skills. If this is the case, then we should expect both the award-winning outcomes and the stock-return outperformance of a firm to be persistent because they are driven by the firm's persistent omitted characteristics. In other words, following this argument, the award-winning outcomes should not only predict but also concur with stock-return outperformance.

To address such omitted variable concern, we use the future award-wining outcomes to define *pseudo* awarded and unawarded firms in the present. Specifically, we define a firm as *pseudo*-awarded in year *t* if it receives at least one award from year *t*+1 to year *t*+5 and a firm as *pseudo*-unawarded in year *t* if it does not receive any award from year *t*+1 to year *t*+5 and is comparable with the *pseudo*-awarded firm in terms of market capitalization, book-to-market ratio, momentum, and R&D intensity. We then construct the *pseudo*-awarded-minus-unawarded (*pseudo*-AMU) portfolio at June of year *t*+1 by going long in the *pseudo*-awarded portfolio and going short in the *pseudo*-unawarded portfolio and allow this *pseudo*-AMU portfolio to perform from July of year *t*+1 to June of year *t*+2. The omitted variable argument points to a positive and statistically significant *pseudo*-AMU portfolio return.

Our empirical results in Table 5, however, yield an opposite pattern. For example, Column (1) implies that the *pseudo*-awarded stocks just slightly outperform the *pseudo*-unawarded stocks by 0.04% per month, but it is statistically insignificant. More interestingly, when we control for well-documented factors, we obtain negative alphas, although insignificant as well.

[Table 5 here.]

Overall, we find evidence consistent with the hypothesis that the awarded firms have higher expected stock returns than their benchmarked unawarded counterparts. We confirm that this outperformance of awarded firms is not driven by other omitted variables. Besides, we find that such an award-return relation lasts up to five years and probably reflects the higher long-term risks of the awarded firms rather than any behavioral bias or market frictions. In the following sections, we implement further tests for our risk-based explanation.

3.2 Future risk exposures and award outcomes

Hypothesis 2 proposes that awarded firms have higher systematic risk exposure. To test it, we first follow the literature of conditional CAPM, such as Jagannathan and Wang (1996), Kumar et al. (2008), Lin and Zhang (2013), Cai et al. (2015), Cederburg and O'Doherty (2016), and Hsu et al. (2016), among others, and use the market beta as a proxy for a firm's systematic risk exposure.[22] We estimate the future market beta for

[22] We are aware of the measurement errors in market beta, as pointed out by Lin and Zhang (2013).

each firm in year t by regressing its monthly excess returns on the market risk factor (MKT) over a rolling-five-year window from year t+1 to t+5. In the sample of our regression, we include each awarded firm (awarded at least once in the previous five years) and its comparable unawarded counterparts that have a similar size, book-to-market ratio, momentum, and R&D intensity, and that are in the same FF12 industry.

In Table 6 Panel A, we compare the future market betas of awarded firms with those of benchmarked unawarded firms and find that the awarded firms on average have significantly higher future market betas. For example, the average future market beta of the awarded firms is 1.16. A t-test indicates that this number is significantly higher than one at the 1% level, which thereby confirms that awarded firms are riskier than "average firms." On the contrary, the average future market beta of the benchmarked unawarded firms is 1.06 and is statistically indifferent from one. The difference in future market beta between the awarded firms and the benchmarked unawarded firms is 0.10, which is significant at the 1% level, and implies that, on average, firms with award-winning innovative products have higher future market betas than their unawarded counterparts. In Figure 4, we illustrate the time-series variation of future market betas for both awarded firms and benchmarked unawarded firms. It shows that the future market betas of the awarded firms (plotted in the solid line) are usually higher than those of the benchmarked unawarded firms (plotted in the dashed line).

[Figure 4 here.]

In Panel B of Table 6, we conduct firm-level panel regressions to further control for firm characteristics correlated to future market betas. Specifically, we include all awarded firms and their benchmarked unawarded firms in the sample and regress the future market betas in year t (estimated from the 60 months from year t+1 to t+5) on a dummy variable indicating whether a firm is an awardee or not in year t. We also control for other firm-level characteristics: the market beta estimated from year t-4 to t, the natural logarithm of market capitalization, the natural logarithm of book-to-market ratio, momentum, R&D expenses, SG&A expenses, and advertising expenses.

Table 6 Panel B confirms that the difference in future market betas between the awarded firms and the benchmarked unawarded firms is not driven by other firm characteristics. For instance, in Column (1) where we only control for previous market betas, the coefficient on the award dummy is 0.11, which is even higher than the beta difference in Panel A. When we further include all firm characteristics in Column (5), the coefficient on the award dummy is 0.13 and significant at the 1% level. This number is economically large: if an unawarded firm is counter-factually recognized by an R&D 100 award, then its future market beta will increase by 12% (=0.13/1.06). When we include all fixed effects, the coefficient drops to 0.09 in Column (8), which is still significant at the 5% level.

[Table 6 here.]

We then directly test our argument that the sales of awarded firms are more procyclical to aggregate consumption than those of their unawarded counterparts. To do so, we measure the future procyclicality of a firm's sales by year t as the correlation between annual sales growth and annual growth of aggregate consumption proxied by expenditures on nondurable goods (Hansen and Singleton (1983); Flavin (1981); Hall (1988); Epstein and Zin (1991)) in the next five years from year t+1 to t+5. In the sample of our regression, we include all awarded firms (awarded at least once in the previous five years) and their comparable unawarded counterparts that have a similar size, book-to-market ratio, momentum, and R&D intensity, and that are in the same FF12 industry.

In Panel A of Table 7, we compare the future procyclicality of awarded firms with that of benchmarked unawarded firms. Our results imply that the awarded firms on average have significantly higher future procyclicality. For example, the average future procyclicality of the awarded firms is 0.31, and the average future procyclicality of the unawarded firms is 0.26, both of which are positive and statistically significant. A further two-sample t-test indicates that the difference between these two numbers is significant at the 1% level, which confirms that the sales growth of awarded firms is more procyclical than that of the unawarded firms. In Figure 5, we observe that the future procyclicality of sales growth of the awarded firms (plotted in the solid line) is usually higher than that of the benchmarked unawarded firms (plotted in the dashed line).

[Table 7 here.]

[Figure 5 here.]

We conduct additional firm-level panel regressions to further control for firm characteristics correlated to future procyclicality. Specifically, we include all awarded firms and their unawarded counterparts in the sample and then regress the future procyclicality by year t (estimated from year t+1 to t+5) on a dummy variable indicating whether a firm is an awardee or not in year t. We also control for other firm-level characteristics, such as the procyclicality estimated from year t-4 to t, the natural logarithm of market capitalization, the natural logarithm of book-to-market ratio, momentum, R&D expenses, SG&A expenses, and advertising expenses.

Table 7 Panel B confirms that the difference in future procyclicality between the awarded firms and the benchmarked unawarded firms is not driven by other firm characteristics. For instance, in Column (1) where we only control for previous procyclicality, the coefficient on the award dummy is 0.07 and statistically significant at the 1% level. When we further include all firm characteristics, year fixed effects, and industry fixed effects in Column (8), the coefficient on the award dummy is 0.04 and is significant at the 5% level. Although this number is smaller than that in Column (1), it is still economically large: if an unawarded firm is counter-factually recognized by an R&D 100 award, then its future procyclicality will increase by 15% (=0.04/0.26).

Overall, our findings using both market beta and correlation between sales growth and aggregate consumption growth as proxies of systemic risk exposure collectively support the risk-based explanation for the award-return relation. Hence, our findings indicate that firms become riskier once they receive innovative product awards.

3.3 The award-return relation and consumption growth

Hypothesis 3 attributes the award-return relation to consumption risks: the award-return relation is procyclical to aggregate consumption. We test it by regressing the monthly AMU portfolio return on contemporary aggregate consumption growth in Table 8. Following Hansen and Singleton (1983), Flavin (1981), Hall (1988), and

Epstein and Zin (1991), we measure aggregate consumption expenditures by the expenditures on nondurable goods and then adjust for the Consumer Price Index. We compute the consumption growth rate in the form of natural logarithm. We also compute the *t*-values under the Newey-West heteroscedasticity and autocorrelation consistent covariance estimation (HAC).

[Table 8 here.]

When we regress the monthly AMU portfolio return on the contemporary consumption growth rate in Column (1), we find a positive coefficient estimate of 0.02, which is statistically significant at the 1% level. This estimate also implies that the procyclicality of the award-return relation is economically considerable: if the total consumption growth increases by one standard deviation (13.21%), then the monthly AMU portfolio return will increase by 0.26% (i.e., 0.02*13.21%) or almost double from the sample average (i.e., 0.28%). The significance of the coefficient estimate is statistically robust and barely changes in magnitude when we control for other systematic asset pricing risk factors, such as the market factor, the size factor, the value factor, the momentum factor, the profitability factor, the investment factor, and the R&D factor.

Generally speaking, these results confirm the procyclicality of the award-return relation and support our consumption-based explanation for the risk premium of award outcomes.

3.4 The award-return relation and R&D investments

The final hypothesis is that the award-return relation is more pronounced for firms with higher R&D investments (Hypothesis 4). To test it, we perform a two-way sequential portfolio sorting analysis to examine the risk premium of awarded firms across different subgroups of R&D intensity.[23] Specifically, at the end of year *t* from

[23] Sequential sorting fits our theoretical setting: we argue that endogenous R&D investment predicts the probability of being awarded, and that the award-return relation strengthens with R&D investments. In our data, we find a positive correlation between R&D investments and award outcomes. As a result, if we employ the standard independent sort procedure, the underlying correlation might lead to suboptimal performance and poor diversification (Lambert and Hubner, 2013; Lambert et al., 2016).

1969 to 2014, these awarded firms (which are awarded at least once in the previous five years) with non-missing R&D values are sorted into five subgroups based on the 20th to 80th percentiles with 20-percentile increments of annual R&D expenditures scaled by total assets at the same fiscal year end. Following the same methodology we used in Section 2, we identify the unawarded counterparts of each awarded firm if these firms have a similar size, book-to-market ratio, momentum, and R&D intensity and are in the same FF12 industry. To compare the difference in expected stock returns of awarded firms and their benchmarked unawarded firms in different subgroups of R&D investments, we construct an awarded-minus-unawarded (AMU) portfolio by going long in the equal-weighted awarded portfolio and going short in the equal-weighted benchmarked unawarded portfolio in each R&D subgroup, and then track the monthly return on this portfolio over the next twelve months from July of year t+1 and June of year t+2.

In Table 9, we report the average monthly excess returns of the AMU portfolio for both subgroups of high and low R&D investments (top 20% and bottom 20%, respectively). We document that the risk premium of awarded firms differs significantly in these two subgroups. For instance, in the high R&D subgroup (above the 80th percentile), the average monthly excess stock return of the awarded portfolio is 1.53%, and that of the benchmarked unawarded portfolio is 0.51%. The difference is 1.01% per month and is statistically significant at the 5% level. However, such a return spread (0.09) is not significant in the low R&D subgroup (below the 20th percentile).

[Table 9 here.]

As we did in Section 3.1, we also control for their exposure to a bunch of systematic risk factors to relieve the concern that the risk premium of awarded firms is driven by higher exposure to certain risk factors.[24] Our results show that under all factor models, the alphas of awarded firms are significant in the high R&D subgroup (presented in the column labelled "High") but are insignificant in the low R&D subgroup (presented in the column labelled "Low"). We then form another portfolio

[24] In Table 9, we only report alphas in all factor models for the interest of space. We present the corresponding factor loadings in our Online Appendix Table OA3.

that takes a long position in the awarded-minus-unawarded portfolio in the high R&D subgroup and takes a short position in the awarded-minus-unawarded portfolio in the low R&D subgroup. The returns and alphas of this portfolio, as shown in the "High-Minus-Low" column, which are all positive. For example, the alpha is 1.04% under the Fama-French three-factor model and 1.13% under the Fama-French six factor model; thus, it appears that controlling for these risk factors does not change our conclusion. In sum, our empirical evidence strongly supports our hypothesis that the award-return relation is more pronounced among R&D-intensive firms.

4 Concluding Remarks

In this paper, we study the asset pricing implications of product market segmentation by focusing on a prestigious award for innovative products: the R&D 100 Award. This award is published by *R&D Magazine* and has received significant publicity for over fifty years. We first document evidence showing that a firm recognized by the award is more likely to have higher product differentiation, to encounter lower product threats, and to achieve higher profitability over the next five-year horizon, which confirms the positive effect of the R&D 100 Award on product performance due to access to high-end markets.

We then propose four testable hypotheses based on the argument that growth opportunities through accessing to high-end markets are associated with higher procyclicality. Empirical evidence first supports the award-return relation: the monthly equal-weighted stock returns of awarded firms outperform their benchmarked counterparts by 0.21% to 0.32%. Our empirical results then support a risk-based explanation of this award-return relation: the awarded firms have significant higher procyclicality of sales growth with respect to aggregate consumption growth by 0.03 to 0.07 and significantly higher market betas by 0.08 to 0.13 than their unawarded benchmarks; these numbers depend on the control variables that we include. Furthermore, the risk premium of awarded firms is procyclical to aggregate consumption growth: if the aggregate consumption growth increases by one standard deviation, then the monthly return on an awarded-minus-unawarded portfolio will increase by 0.26%. Finally, our empirical findings confirm the connection between the award-return relation and firms' growth opportunities: the risk premium associated with the award in the high R&D firms exceeds that in the low R&D firms by 0.81% to 1.30% per month, depending on the factor models that we choose.

Overall, our findings collectively support a role of innovative product awards in asset pricing: these awards enable firms to commercialize their growth opportunities in high-end markets, and such shift in product market segmentation leads to higher systematic, consumption risks that require higher expected stock returns as risk premium.

References

Abel, A.B., Eberly, J.C., 2011. How q and cash flow affect investment without frictions: An analytic explanation. Rev. Econ. Stud. 78, 1179-1200.

Aguerrevere, F.L., 2009. Real options, product market competition, and asset returns. J. Finance 64, 957-983.

Ai, H., Kiku, D., 2013. Growth to value: option exercise and the cross section of equity returns. J. Financ. Econ. 107, 325-349.

Ait-Sahalia, Y., Parker, J.A., Yogo, M., 2004. Luxury goods and the equity premium. J. Finance 59, 2959-3004.

Belo, F., Lin, X., Vitorino, M.A., 2014. Brand capital and firm value. Rev. Econ. Dynam. 17, 150-169.

Berk, J.B., Green, R.C., Naik, V., 1999. Optimal investment, growth options, and security returns. J. Finance 54, 1553-1607.

Block, F., Keller, M.R., 2009. Where do innovations come from? Transformations in the US economy, 1970–2006. Socio-Econ. Rev. 7, 459-483.

Bloom, N., Reenen, J.V., 2002. Patents, real options and firm performance. Econ. J. 112, C97–C116.

Brennan, M.J., Chordia, T., Subrahmanyam, A., 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns1. J. Financ. Econ. 49, 345-373.

Cai, Z., Ren, Y., Yang, B., 2015. A semiparametric conditional capital asset pricing model. J. Bank. Financ. 61, 117-126.

Campbell, J.Y., Cochrane, J.H., 1999. By force of habit: A consumption-based explanation of aggregate stock market behavior. J. Polit. Econ. 107, 205-251.

Carhart, M.M., 1997. On persistence in mutual fund performance. J. Finance 52, 57-82.

Carlson, M., Fisher, A., Giammarino, R., 2004. Corporate investment and asset price dynamics: implications for the cross-section of returns. J. Finance 59, 2577-2603.

Cederburg, S., O'Doherty, M.S., 2016. Does it pay to bet against beta? on the conditional performance of the beta anomaly. J. Finance 71, 737-774.

Chambers, D., Jennings, R., Thompson, R.B., 2002. Excess returns to R&D-intensive firms. Rev. Account. Stud. 7, 133-158.

Chan, L.K.C., Lakonishok, J., Sougiannis, T., 2001. The stock market valuation of research and development expenditures. J. Finance 56, 2431-2456.

Chapman, D.A., 1998. Habit formation and aggregate consumption. Econometrica 66, 1223-1230.

Chen, I.J., Hsu, P.-H., Officer, M.S., Wang, Y., 2017. The Oscar goes to…: takeovers and innovation envy. Working Paper.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. J. Finance 52, 1035-1058.

Deng, Z., Lev, B., Narin, F., 1999. Science and technology as predictors of stock performance. Financ. Anal. J. 55, 20-32.

Epstein, L.G., Zin, S.E., 1991. Substitution, risk aversion, and the temporal behavior of consumption and asset returns: An empirical analysis. J. Polit. Econ. 99, 263-286.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33, 3-56.

Fama, E.F., French, K.R., 1995. Size and book-to-market factors in earnings and returns. J. Finance 50, 131-155.

Fama, E.F., French, K.R., 2015. Incremental variables and the investment opportunity set. J. Financ. Econ. 117, 470-488.

Fama, E.F., French, K.R., 2017. International tests of a five-factor asset pricing model. J. Financ. Econ. 123, 441-463.

Flavin, M.A., 1981. The adjustment of consumption to changing expectations about future income. J. Polit. Econ. 89, 974-1009.

Garleanu, N., Panageas, S., Yu, J., 2012. Technological growth and asset pricing. J. Finance 67, 1265-1292.

Greenwood, J., Hercowitz, Z., Krusell, P., 2001. Long-run implication of investment-specific technological change. Amer. Econ. Rev. 87, 342-362.

Hall, R.E., 1988. Intertemporal substitution in consumption. J. Polit. Econ. 96, 339-357.

Hansen, L.P., Singleton, K.J., 1983. Stochastic consumption, risk aversion, and the temporal behavior of asset returns. J. Polit. Econ. 91, 249-265.

Hirshleifer, D., Hsu, P.-H., Li, D., 2013. Innovative efficiency and stock returns. J. Financ. Econ. 107, 632-654.

Hoberg, G., Phillips, G., 2016. Text-based network industries and endogenous product differentiation. J. Polit. Econ. 124, 1423-1465.

Hoberg, G., Phillips, G., Prabhala, N., 2014. Product market threats, payouts, and financial flexibility. J. Finance 69, 293-324.

Hobijn, B., Jovanovic, B., 2001. The information-technology revolution and the stock market: evidence. Amer. Econ. Rev. 91, 1203-1220.

Hsu, P.-H., 2009. Technological innovations and aggregate risk premiums. J. Financ. Econ. 94, 264-279.

Hsu, P.-H., Lee, H.-H., Zhou, T., 2016. Falling into traps? Patent thickets and stock returns. Working Paper.

Jagannathan, R., Wang, Z., 1996. The conditional CAPM and the cross-section of expected returns. J. Finance 51, 3-53.

Kogan, L., 2004. Asset prices and real investment. J. Financ. Econ. 73, 411-431.

Kogan, L., Papanikolaou, D., 2014. Growth opportunities, technology shocks, and asset prices. J. Finance 69, 675-718.

Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation, and growth. Quart. J. Econ. 132, 665-712.

Kumar, P., Sorescu, S.M., Boehme, R.D., Danielsen, B.R., 2008. Estimation risk, information, and the conditional CAPM: Theory and evidence. Rev. Financ. Stud. 21, 1037-1075.

Laitner, J., Stolyarov, D., 2003. Technological change and the stock market. Amer. Econ. Rev. 93, 1240-1267.

Lambert, M., Fays, B., Hubner, G., 2016. Size and value matter, but not the way you thought. Working Paper.

Lambert, M., Hubner, G., 2013. Comoment risk and stock returns. J. Emp. Financ. 23, 191-205.

Lev, B., Sougiannis, T., 1996. The capitalization, amortization, and value-relevance of R&D. J. Acc. Econ. 21, 107-138.

Li, D., 2011. Financial constraints, R&D investment, and stock returns. Rev. Financ. Stud. 24, 2974-3007.

Lin, X., 2012. Endogenous technological progress and the cross-section of stock returns. J. Financ. Econ. 103, 411-427.

Lin, X., Zhang, L., 2013. The investment manifesto. J. Monet. Econ. 60, 351-366.
McGahan, A.M., Silverman, B.S., 2001. How does innovative activity change as industries mature? Int. J. Ind. Organ. 19, 1141-1160.
Mehra, R., Prescott, E.C., 1985. The equity premium: A puzzle. J. Monet. Econ. 15, 145-161.
Narin, F., Noma, E., Perry, R., 1987. Patents as indicators of corporate technological strength. Res. Pol. 16, 143-155.
Pakes, A., 1985. On patents, R&D, and the stock market rate of return. J. Polit. Econ. 93, 390-409.
Papanikolaou, D., 2011. Investment shocks and asset prices. J. Polit. Econ. 119, 639-685.
Pastor, L., Veronesi, P., 2009. Learning in financial markets. Annu. Rev. Financ. Econ. 1, 361-381.
Verhoeven, D., Bakker, J., Veugelers, R., 2016. Measuring technological novelty with patent-based indicators. Res. Pol. 45, 707-723.
Vitorino, M.A., 2013. Understanding the effect of advertising on stock returns and firm value: theory and evidence from a structural model. Manag. Sci. 60, 227-245.
Zhang, L., 2005. The value premium. J. Finance 60, 67-103.
Zhou, T., 2017. Medical innovation, labor productivity, and the cross section of stock returns. Working Paper.

Tables

Table 1: Summary Statistics of R&D 100 Awards

We manually collect award-winning information about the R&D 100 Award, one of the most prestigious innovative product competitions. The original sampling period for the R&D 100 Award ranges from 1965 to 2014. The sample period is 1969-2014 because the award data is collected from 1965 and our sample of awarded firms is based on a rolling five-year window. We merge the awardees' data with the U.S. public firms' data by manually matching the awarded companies' names and their PERMNO in the Center for Research in Security Prices (CRSP) dataset and GVKEY in the Compustat dataset. To identify comparable benchmarks for awarded firms, we adopt the enhanced characteristic-based sorting method: we restrict the award firms (*Awarded*) and the benchmarked unawarded firms (*Unawarded*) to be 1) in the same quintile in terms of market capitalization, book-to-market ratio, and momentum, 2) within the range of [-1%, +1%] with respect to R&D over the total assets ratio by the end of each fiscal year, and 3) in the same Fama-French 12-industry (FF12) classification. Considering that the effect of the award on the firm may be long-lasting, we further define a firm as awarded if it receives at least one award in the previous five years. In Panel A, we summarize the basic statistics of the five-year matched sample. *Awarded#* and *Unawarded#* report the average number of firms each sample year in the *Awarded* and *Unawarded* groups, respectively. *Total#* is the average number of firms entering our sample each year. *Annual Awarded/Unawarded by Industry* report the average ratios of *Awarded* over *Unawarded* by industry. In Panel B, we compare the mean characteristics between awarded firms and their unawarded benchmarks. To mitigate any bias due to extreme industry-year observations, we compute the mean characteristics by first averaging within each industry-year, then averaging across all sample years, and finally averaging across all industries. We consider firm characteristics such as market capitalization (*Market Cap*, in billions), book-to-market ratio (*B/M*), momentum (eleven-month accumulative stock return with the gap of the most recent month), total assets (in billions), the ratio of R&D over total assets (*R&D Intensity*), the ratio of capital expenditures over total assets (*Capex*), the ratio of costs of selling, general, and administration over total assets (*SG&A*), the ratio of advertisement expenses over total assets (*Advertising*), return on equity (*ROE*) as defined as net profit divided by the market value of equity, and the ratio of net sales over total assets (*Sales*).

Panel A: Five-year Computed Measures

Awarded #	Unawarded #	Total #	Annual Awarded/Unawarded by Industry		
			Mean	Median	Std dev.
31	49	80	0.94	1.00	0.63

Panel B: Characteristics of Awarded Firms vs. Unawarded Firms

Group	Market Cap	B/M	Momentum	Total Assets	R&D Intensity
Unawarded	4454.47	0.73	0.19	4.32	0.05
Awarded	7373.00	0.75	0.15	8.94	0.05

Group	Capex	SG&A	Advertising	ROE	Sales
Unawarded	0.06	0.26	0.04	0.04	1.07
Awarded	0.06	0.25	0.03	0.04	1.04

Table 2: Future Product Market Performances and Award Outcomes

By the end of fiscal year *t*, we identify awarded firms and their unawarded matched counterparts following the method that we used in Table 1. In Panels A1, B1, and C1, we compare the future five-year (from year *t*+1 to *t*+5) arithmetic average total similarity score, the product fluidity score, and the return on equity (ROE) of the awarded firms with those of the unawarded firms, respectively. The total similarity score and product fluidity score follow Hoberg and Phillips (2016) and Hoberg et al. (2014), respectively, and are computed based on the text analyses of product announcements. The statistical difference in the time-series average of the future total similarity score, product fluidity score, and ROE between the awarded group and unawarded group is tested using a paired-sample *t*-test. In Panels A2, B2, and C2, we respectively regress the future five-year (from year *t*+1 to *t*+5) arithmetic average total similarity score, product fluidity score, and ROE on a dummy variable indicating whether a firm is identified as awarded or not at year *t*, respectively. ROE is defined as the net profit divided by the market value of equity. Our panel regressions consider control variables at year *t*, including the lagged variable of interest, natural logarithm of market capitalization (*ln(Size)*), natural logarithm of book-to-market ratio (*ln(B/M)*), momentum (*MOM*), R&D expenses (in trillions), SG&A expenses (in trillions), advertising expenses (in trillions), year fixed effects, and industry fixed effects according to the Fama-French 12-industry classification. The sample period of total similarity and product fluidity is 1997-2014, and the sample period of ROE is 1969-2014. Numbers without parentheses report parameter estimates, and numbers with parentheses show robust *t*-values clustered by industry and year. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

(Table 2 continued)

Panel A: Future Total Similarity

Panel A1: T-test of Future Total Similarity

Variable \ Groups	Awarded	Unawarded	Awarded-Minus-Unawarded
Total Similarity	2.58***	3.47***	-0.89***
	(21.60)	(15.83)	(-3.97)

Panel A2: Panel Regressions of Future Total Similarity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Awarded	-0.10**	-0.14***	-0.18***	-0.19***	-0.15***	-0.17***	-0.18***	-0.18***
	(-2.82)	(-4.68)	(-3.70)	(-4.04)	(-3.59)	(-4.40)	(-3.26)	(-3.32)
Current Total Similarity	0.95***	0.96***	0.94***	0.94***	0.93***	0.94***	0.92***	0.93***
	(14.48)	(14.58)	(15.70)	(16.01)	(15.49)	(15.71)	(16.31)	(16.78)
ln(Size)					-0.05***	-0.05**	-0.01	-0.03
					(-3.12)	(-2.95)	(-0.51)	(-1.25)
ln(B/M)					-0.15**	-0.15***	0.01	-0.05
					(-2.90)	(-3.81)	(0.15)	(-0.66)
MOM					0.02	0.01	0.02	0.01
					(0.53)	(0.23)	(0.37)	(0.27)
R&D Expenses					0.14**	0.11*	0.08	0.08
					(2.60)	(2.10)	(1.55)	(1.36)
SG&A Expenses					-0.00	-0.00	-0.02	-0.02
					(-0.32)	(-0.32)	(-1.13)	(-0.90)
Advertising Expenses					-0.04	0.02	-0.01	0.03
					(-0.48)	(0.31)	(-0.14)	(0.37)
Observations	831	831	831	831	831	831	831	831
R-squared	0.87	0.88	0.88	0.89	0.87	0.88	0.88	0.89
Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES	NO	NO	YES	YES

(Table 2 continued)

Panel B: Future Fluidity

Panel B1: T-test of Future Fluidity

Variable \ Groups	Awarded	Unawarded	Awarded-Minus-Unawarded
Fluidity	3.79***	3.99***	-0.20*
	(42.98)	(33.22)	(-1.86)

Panel B2: Panel Regressions of Future Fluidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Awarded	-0.06***	-0.05***	-0.03***	-0.02***	-0.05***	-0.05***	-0.04**	-0.04**
	(-29.97)	(-8.81)	(-27.56)	(-8.55)	(-3.50)	(-5.37)	(-2.77)	(-2.29)
Current Fluidity	0.48***	0.49***	0.44***	0.45***	0.48***	0.48***	0.44***	0.45***
	(13.04)	(12.67)	(12.57)	(12.29)	(12.80)	(12.87)	(12.04)	(12.08)
ln(Size)					0.02	0.03	-0.00	0.03
					(0.79)	(0.87)	(-0.07)	(0.55)
ln(B/M)					-0.12*	-0.13**	-0.12	-0.10*
					(-2.15)	(-2.41)	(-1.69)	(-2.12)
MOM					-0.00	-0.01	0.00	-0.00
					(-0.05)	(-0.29)	(0.04)	(-0.08)
R&D Expenses					-0.01	-0.01	0.03	0.01
					(-0.66)	(-0.47)	(0.62)	(0.17)
SG&A Expenses					0.01	0.01	0.01	0.01
					(0.57)	(0.96)	(0.81)	(1.23)
Advertising Expenses					-0.06***	-0.05***	-0.07***	-0.06***
					(-3.76)	(-3.30)	(-4.26)	(-4.36)
Observations	769	769	769	769	769	769	769	769
R-squared	0.74	0.76	0.76	0.78	0.75	0.77	0.77	0.78
Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES	NO	NO	YES	YES

(Table 2 continued)

Panel C: Future Return on Equity (ROE)

Panel C1: T-test of Future ROE

Variable \ Groups	Awarded	Unawarded	Awarded-Minus-Unawarded
ROE	0.04***	0.01*	0.02***
	(5.05)	(1.87)	(3.69)

Panel C2: Panel Regressions of Future ROE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Awarded	0.02**	0.02**	0.02**	0.02***	0.02**	0.01*	0.01**	0.01**
	(2.82)	(2.87)	(2.95)	(5.38)	(3.10)	(1.86)	(2.77)	(2.87)
Current ROE	0.12***	0.10**	0.09***	0.07**	0.09***	0.05*	0.08**	0.05*
	(3.65)	(2.56)	(3.56)	(2.25)	(3.18)	(2.01)	(2.91)	(1.87)
ln(Size)					0.01**	0.02***	0.01*	0.01***
					(3.02)	(6.35)	(2.21)	(4.59)
ln(B/M)					0.02***	0.00	0.01**	-0.01*
					(5.59)	(0.19)	(2.86)	(-1.92)
MOM					0.01*	0.01	0.01**	0.01*
					(2.03)	(1.80)	(2.80)	(1.83)
R&D Expenses					-0.02**	-0.02**	-0.00	-0.01
					(-2.34)	(-2.27)	(-0.55)	(-1.14)
SG&A Expenses					0.00	-0.00	0.00	-0.00
					(1.46)	(-0.60)	(0.31)	(-0.23)
Advertising Expenses					0.01	0.01	-0.00	0.01
					(0.71)	(1.00)	(-0.19)	(0.98)
Observations	2,793	2,793	2,793	2,793	2,793	2,793	2,793	2,793
R-squared	0.02	0.09	0.08	0.13	0.04	0.14	0.08	0.15
Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES	NO	NO	YES	YES

Table 3: Future Stock Returns and Award Outcomes

We examine the relation between award outcomes and future stock returns. To do so, in June of year *t*+1, we construct an awarded portfolio taking equal weights on all awarded firms at the end of year *t*-1 and hold this portfolio from July of year *t*+1 to June of year *t*+2. We further define a firm as awarded by the end of year *t*-1 if it receives at least one award in the previous five years from year *t*-4 to *t*. To test the statistical significance of abnormal returns adjusted for the exposure to risk factors, we compute the portfolio monthly return in excess of the risk-free interest rate (*excess return*) in Model (1), and regress these excess returns on risk factors, such as the market factor (*MKT*) in the capital asset pricing model (*CAPM*) in Model (2), the size factor (*SMB*) and the value factor (*HML*) in the three-factor model (*FF3*) by Fama and French (1993) in Model (3), the momentum factor (*UMD*) in the four-factor model (*FF4*) by Carhart (1997) in Model (5), the profitability factor (*RMW*) and the investment factor (*CMA*) in the five-factor model (*FF5*) by Fama and French (2015) in Model (7). In Model (9), we construct a Fama and French (2017) six-factor model (*FF6*) that includes *MKT*, *SMB*, *HML*, *RMW*, *CMA*, and *UMD*. Besides, we also augment these factor models with the R&D factor (*XRDF*) following Chan et al. (2001) in Models (4), (6), (8), and (10). The monthly returns are from July of 1970 to June of 2016. Numbers without parentheses report parameter estimates of excess return and their corresponding alphas and betas, and numbers with parentheses show *t*-values. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively. All estimates are in percentage.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Excess return /Alpha	0.97***	0.29**	0.21**	0.17**	0.30***	0.25***	0.21**	0.15*	0.29***	0.22***
	(3.78)	(2.49)	(2.34)	(2.12)	(3.46)	(3.08)	(2.29)	(1.76)	(3.23)	(2.61)
MKT		1.20***	1.11***	1.07***	1.08***	1.05***	1.11***	1.08***	1.10***	1.07***
		(47.46)	(54.19)	(55.06)	(53.33)	(54.43)	(51.39)	(52.49)	(51.71)	(52.82)
SMB			0.59***	0.45***	0.59***	0.46***	0.57***	0.46***	0.57***	0.46***
			(20.26)	(14.63)	(20.67)	(15.09)	(18.45)	(14.40)	(19.02)	(14.97)
HML			0.03	-0.04	-0.01	-0.07**	-0.01	-0.08**	-0.09**	-0.13***
			(1.01)	(-1.40)	(-0.23)	(-2.28)	(-0.34)	(-1.99)	(-2.01)	(-3.30)
UMD					-0.11***	-0.09***			-0.12***	-0.09***
					(-5.44)	(-4.61)			(-5.76)	(-5.00)
RMW							-0.07*	0.02	-0.05	0.03
							(-1.72)	(0.39)	(-1.16)	(0.77)
CMA							0.11*	0.08	0.18***	0.14**
							(1.78)	(1.41)	(2.84)	(2.35)
XRDF				0.19***		0.18***		0.19***		0.18***
				(9.51)		(9.01)		(9.18)		-8.68
Obs (# of months)	552	552	552	552	552	552	552	552	552	552
R-squared		0.80	0.89	0.89	0.89	0.90	0.90	0.91	0.90	0.91

Table 4: One-Way Portfolio Sorting with Unawarded Benchmarks

We benchmark the award-return relation with the comparable unawarded stocks. To do so, we construct an awarded-minus-unawarded (*AMU*) portfolio at June of year *t*+1 by going long in the awarded portfolio and going short in the unawarded portfolio and allow it to perform from July of year *t*+1 to June of year *t*+2. The awarded and unawarded portfolio take equal weights on the awarded and unawarded stocks, respectively. The awarded and unawarded stocks are identified following the methodology that we used in Table 1. To test the statistical significance of abnormal returns adjusted for the exposure to risk factors, we compute the portfolios' monthly return in excess of the risk-free interest rate (*excess return*) in Model (1), and regress these excess returns on risk factors, such as the market factor (*MKT*) in the capital asset pricing model (*CAPM*) in Model (2), the size factor (*SMB*) and the value factor (*HML*) in the three-factor model (*FF3*) by Fama and French (1993) in Model (3), the momentum factor (*UMD*) in the four-factor model (*FF4*) by Carhart (1997) in Model (5), the profitability factor (*RMW*) and the investment factor (*CMA*) in the five-factor model (*FF5*) by Fama and French (2015) in Model (7). In Model (9), we construct a Fama and French (2017) six-factor model (*FF6*) that includes *MKT*, *SMB*, *HML*, *RMW*, *CMA*, and *UMD*. Besides, we also augment these factor models with the R&D factor (*XRDF*) following Chan et al. (2001) in Models (4), (6), (8), and (10). The monthly returns are from July of 1970 to June of 2016. Numbers without parentheses report parameter estimates of excess return and their corresponding alphas and betas, and numbers with parentheses show *t*-values. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively. All estimates are in percentage.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Excess return /Alpha	0.28**	0.25**	0.32**	0.30**	0.23*	0.21*	0.32**	0.31**	0.26**	0.23*
	(2.30)	(2.03)	(2.57)	(2.48)	(1.84)	(1.66)	(2.56)	(2.43)	(2.01)	(1.80)
MKT		0.06**	0.04	0.03	0.06**	0.05*	0.05	0.04	0.06**	0.05
		(2.09)	(1.57)	(1.06)	(2.25)	(1.71)	(1.60)	(1.24)	(2.04)	(1.63)
SMB			-0.07*	-0.12***	-0.07*	-0.13***	-0.10**	-0.13***	-0.10**	-0.14***
			(-1.80)	(-2.66)	(-1.75)	(-2.85)	(-2.32)	(-2.85)	(-2.37)	(-3.09)
HML			-0.14***	-0.16***	-0.10**	-0.13***	-0.18***	-0.20***	-0.12**	-0.14**
			(-3.13)	(-3.61)	(-2.29)	(-2.86)	(-3.09)	(-3.36)	(-1.99)	(-2.29)
UMD					0.10***	0.11***			0.10***	0.11***
					(3.43)	(3.77)			(3.42)	(3.69)
RMW							-0.09	-0.07	-0.11*	-0.08
							(-1.59)	(-1.13)	(-1.96)	(-1.41)
CMA							0.11	0.10	0.06	0.04
							(1.27)	(1.17)	(0.65)	(0.47)
XRDF				0.07**		0.08***		0.05*		0.07**
				(2.23)		(2.72)		(1.78)		(2.25)
Obs (# of months)	552	552	552	552	552	552	552	552	552	552
R-squared		0.01	0.03	0.05	0.04	0.06	0.04	0.06	0.04	0.07

Table 5: Falsification Test of Award-Return Relation

We define a firm as *pseudo*-awarded if it receives at least one award from year *t*+1 to year *t*+5. We benchmark the award-return relation with the comparable unawarded stocks. To do so, we construct a *pseudo*-awarded-minus-unawarded (*pseudo-AMU*) portfolio at June of year *t*+1 by going long in the *pseudo*-awarded portfolio and going short in the *pseudo*-unawarded portfolio and allow it to perform from July of year *t*+1 to June of year *t*+2. The *pseudo*-awarded and *pseudo*-unawarded portfolio take equal weights on the *pseudo*-awarded and *pseudo*-unawarded stocks, respectively. The *pseudo*-unawarded stocks are the stocks that do not receive any award from year *t*+1 to year *t*+5 but are highly comparable to the awarded firms, according to the methodology that we used in Table 1. To test the statistical significance of abnormal returns adjusted for the exposure to risk factors, we compute the portfolios' monthly return in excess of the risk-free interest rate (*excess return*) in Model (1), and regress these excess returns on risk factors, such as the market factor (*MKT*) in the capital asset pricing model (*CAPM*) in Model (2), the size factor (*SMB*) and the value factor (*HML*) in the three-factor model (*FF3*) by Fama and French (1993) in Model (3), the momentum factor (*UMD*) in the four-factor model (*FF4*) by Carhart (1997) in Model (5), the profitability factor (*RMW*) and the investment factor (*CMA*) in the five-factor model (*FF5*) by Fama and French (2015) in Model (7). In Model (9), we construct a Fama and French (2017) six-factor model (*FF6*) that includes *MKT*, *SMB*, *HML*, *RMW*, *CMA*, and *UMD*. Besides, we also augment these factor models with the R&D factor (*XRDF*) following Chan et al. (2001) in Models (4), (6), (8), and (10). The monthly returns are from July of 1970 to June of 2016. Numbers without parentheses report parameter estimates of excess return and their corresponding alphas and betas, and numbers with parentheses show *t*-values. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively. All estimates are in percentage.

(Table 5 continued)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Excess return /Alpha	0.04	-0.02	0.02	-0.01	0.01	-0.04	-0.03	-0.08	-0.04	-0.10
	(0.28)	(-0.15)	(0.17)	(-0.06)	(0.04)	(-0.31)	(-0.22)	(-0.62)	(-0.27)	(-0.76)
MKT		0.13***	0.14***	0.10***	0.14***	0.11***	0.16***	0.12***	0.16***	0.13***
		(4.63)	(4.69)	(3.54)	(4.72)	(3.68)	(5.02)	(4.06)	(5.02)	(4.12)
SMB			-0.10**	-0.23***	-0.10**	-0.23***	-0.09**	-0.21***	-0.09**	-0.21***
			(-2.40)	(-5.00)	(-2.40)	(-5.06)	(-2.05)	(-4.54)	(-2.06)	(-4.59)
HML			-0.04	-0.10**	-0.03	-0.09*	-0.11*	-0.17***	-0.10*	-0.16***
			(-0.87)	(-2.20)	(-0.72)	(-1.93)	(-1.81)	(-2.91)	(-1.68)	(-2.62)
UMD					0.02	0.03			0.01	0.02
					(0.57)	(1.20)			(0.28)	(0.83)
RMW							0.05	0.10*	0.05	0.10*
							(0.85)	(1.79)	(0.80)	(1.68)
CMA							0.15*	0.16*	0.15*	0.15*
							(1.73)	(1.82)	(1.67)	(1.68)
XRDF				0.17***		0.17***		0.17***		0.18***
				(5.80)		(5.89)		(5.97)		(6.02)
Obs (# of months)	552	552	552	552	552	552	552	552	552	552
R-squared		0.04	0.05	0.05	0.05	0.05	0.10	0.11	0.11	0.11

Table 6: Future Five-year Market Betas and Award Outcomes

In Panel A, we compare the average future five-year market betas of the awarded firms with those of the unawarded firms. Specifically, by the end of fiscal year *t*, we identify awarded firms and their unawarded matched counterparts following the methodology that we used in Table 1. To compare the difference in future five-year market betas of the two groups, we first estimate the future market beta in year *t* for each awarded/unawarded stock by regressing this stock's monthly excess return on the market factor (*MKT*) in the future five years from year *t*+1 to *t*+5; we then take the simple equal-weighted average of these future market betas of all stocks in each group as the future market beta of this group. The statistical difference in the time-series average of future five-year market betas between the awarded group and unawarded group is tested using a paired-sample *t*-test. ###, ##, and # indicate significance levels of 1%, 5%, and 10%, respectively, under the null hypothesis that market beta equals one. In Panel B, we regress a firm's future market beta from year *t*+1 to *t*+5 on a dummy variable indicating whether this firm is identified as awarded or not at the end of year *t*. We also control for other variables at year *t*, such as the previous five-year market beta, natural logarithm of market capitalization (*ln(Size)*), natural logarithm of book-to-market ratio (*ln(B/M)*), momentum (*MOM*), R&D expenses (in trillions), SG&A expenses (in trillions), advertising expenses (in trillions), year fixed effects, and industry fixed effects according to the Fama-French 12-industry classification. Numbers without parentheses report parameter estimates, and numbers with parentheses show robust *t*-values clustered by industry and year. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively, under the null hypothesis that the coefficient equals zero.

(Table 6 continued)

Panel A: T-test of Future Market Beta

Variable \ Groups	Awarded	Unawarded	Awarded-Minus-Unawarded
Market Beta	$1.16^{\#\#\#}$	1.06	0.10***
	(5.17)	(1.41)	(3.35)

Panel B: Panel Regressions of Future Market Beta

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Awarded	0.11***	0.09**	0.09***	0.08**	0.13***	0.12***	0.09**	0.09**
	(3.01)	(2.47)	(2.85)	(2.44)	(3.28)	(3.41)	(2.40)	(2.63)
Current Market Beta	0.42***	0.40***	0.33***	0.32***	0.40***	0.38***	0.35***	0.33***
	(8.20)	(8.25)	(8.01)	(8.12)	(8.71)	(8.53)	(8.14)	(8.38)
ln(Size)					-0.03**	-0.04***	-0.02	-0.04
					(-2.45)	(-3.74)	(-0.87)	(-1.55)
ln(B/M)					-0.08**	-0.08*	-0.03	-0.04
					(-2.15)	(-1.70)	(-0.87)	(-0.88)
MOM					-0.03	-0.04	-0.06	-0.05
					(-0.82)	(-1.22)	(-1.40)	(-1.32)
R&D Expenses					0.08***	0.06**	0.11***	0.10***
					(3.07)	(2.20)	(3.69)	(3.66)
SG&A Expenses					-0.01	-0.01	-0.01	-0.01
					(-1.01)	(-1.10)	(-1.10)	(-1.51)
Advertising Expenses					-0.12***	-0.11***	-0.17***	-0.16***
					(-2.82)	(-3.03)	(-2.98)	(-4.30)
Observations	3,376	3,376	3,376	3,376	3,376	3,376	3,376	3,376
R-squared	0.11	0.14	0.16	0.20	0.12	0.16	0.17	0.20
Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES	NO	NO	YES	YES

Table 7: Procyclicality of Sales Growths and Award Outcomes

In Panel A, we compare the future five-year procyclicality of sales growth of the awarded firms with that of the unawarded firms. Specifically, by the end of fiscal year *t*, we identify awarded firms and their unawarded matched counterparts following the methodology that we used in Table 1. To compare the difference in future five-year procyclicality of sales growth of the two groups, we first estimate the future procyclicality of sales growth in year *t* for each awarded/unawarded stock by computing the correlation between annual sales growth and contemporary annual seasonally adjusted consumption growth in the future five years from year *t*+1 to *t*+5; we then take the simple equal-weighted average of the future procyclicality of sales growth of all stocks in each group as the future procyclicality of sales growth of this group. The consumption expenditures are measured as the expenditures on nondurable goods, adjusted for both seasonality and the Consumer Price Index (Hansen and Singleton (1983), Flavin (1981), Hall (1988), and Epstein and Zin (1991)). The sales growth and consumption growth are calculated in the form of natural logarithm. The statistical difference in the time-series average of future procyclicality of sales growth between the awarded group and unawarded group is tested using a paired-sample *t*-test. In Panel B, we regress a firm's future procyclicality of sales growth estimated from year *t*+1 to *t*+5 on a dummy variable indicating whether this firm is identified as awarded or not at the end of year *t*. We also control for other variables at year *t*, such as the previous five-year procyclicality of sales growth estimated from year *t*-4 to *t*, natural logarithm of market capitalization (*ln(Size)*), natural logarithm of book-to-market ratio (*ln(B/M)*), momentum (*MOM*), R&D expenses (in trillions), SG&A expenses (in trillions), advertising expenses (in trillions), year fixed effects, and industry fixed effects according to the Fama-French 12-industry classification. Numbers without parentheses report parameter estimates, and numbers with parentheses show robust *t*-values clustered by industry and year. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively, under the null hypothesis that the coefficient equals zero.

(Table 7 continued)

Panel A: T-test of Procyclicality of Sales Growth			
Variable \ Groups	**Awarded**	**Unawarded**	**Awarded-Minus-Unawarded**
Procyclicality	0.31***	0.26***	0.06***
	(14.53)	(11.51)	(3.09)

Panel B: Panel Regressions of Procyclicality of Sales Growth								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Awarded	0.07***	0.05***	0.04**	0.03*	0.06***	0.05**	0.04**	0.04**
	(3.45)	(2.70)	(2.30)	(1.79)	(3.04)	(2.41)	(2.11)	(1.96)
Current Procyclicality	0.08***	0.07***	0.07***	0.07***	0.08***	0.07***	0.06***	0.06***
	(4.32)	(3.81)	(3.52)	(3.39)	(4.17)	(3.55)	(3.30)	(3.15)
ln(Size)					0.01***	0.02***	0.01	0.00
					(3.00)	(3.77)	(1.03)	(0.24)
ln(B/M)					0.02	0.04**	0.03**	0.05***
					(1.63)	(2.50)	(2.07)	(3.20)
MOM					-0.02	-0.01	-0.03	-0.01
					(-1.60)	(-0.97)	(-1.41)	(-0.43)
R&D Expenses					0.00	-0.00	0.01	0.01
					(0.29)	(-0.28)	(0.88)	(0.42)
SG&A Expenses					0.00	-0.00	-0.00	-0.00
					(0.02)	(-0.70)	(-0.16)	(-0.76)
Advertising Expenses					-0.00	0.00	-0.01	-0.01
					(-0.07)	(0.03)	(-0.37)	(-0.46)
Observations	3,082	3,082	3,082	3,082	3,082	3,082	3,082	3,082
R-squared	0.01	0.07	0.09	0.13	0.02	0.08	0.09	0.14
Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES	NO	NO	YES	YES

Table 8: Procyclicality of Award-Return Relation to Consumption Growth

We examine the procyclicality of the award-return relation to aggregate consumption growth from July 1970 to June 2016. To do so, we regress the monthly awarded-minus-unawarded (*AMU*) spread that we constructed in Table 4 on the monthly aggregate consumption growth adjusted for both seasonality and the Consumer Price Index. The aggregate consumption expenditures are measured by the expenditures on nondurable goods, following Hansen and Singleton (1983), Flavin (1981), Hall (1988), and Epstein and Zin (1991). The consumption growth rate is computed in the form of natural logarithm. We also control for the market factor (*MKT*) in the capital asset pricing model (*CAPM*), the size factor (*SMB*) and the value factor (*HML*) in the three-factor model by Fama and French (1993), the momentum factor (*UMD*) in the four-factor model by Carhart (1997), the profitability factor (*RMW*) and the investment factor (*CMA*) in the five-factor model by Fama and French (2015), and the R&D factor (*XRDF*), following Chan et al. (2001). The *t*-values are computed under the Newey-West heteroscedasticity and autocorrelation consistent covariance estimation (HAC). Numbers without parentheses report parameter estimates, and numbers with parentheses show robust *t*-values. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

AMU Spread	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Aggregate Consumption Growth	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(3.90)	(4.47)	(3.04)	(3.18)	(4.01)	(4.41)	(2.86)	(3.01)	(3.71)	(4.10)
MKT		0.06*	0.05	0.03	0.07**	0.05	0.05	0.04	0.07*	0.05
		(1.83)	(1.42)	(0.96)	(2.04)	(1.55)	(1.45)	(1.14)	(1.85)	(1.49)
SMB			-0.07	-0.12*	-0.07	-0.13**	-0.10*	-0.13**	-0.10**	-0.14**
			(-1.16)	(-1.88)	(-1.19)	(-2.14)	(-1.90)	(-2.24)	(-1.99)	(-2.52)
HML			-0.13**	-0.16**	-0.09	-0.12**	-0.18**	-0.20***	-0.12*	-0.13**
			(-2.01)	(-2.38)	(-1.59)	(-2.04)	(-2.32)	(-2.60)	(-1.68)	(-1.97)
UMD					0.10**	0.11***			0.10**	0.11***
					(2.39)	(2.72)			(2.47)	(2.75)
RMW							-0.09	-0.07	-0.11	-0.08
							(-1.20)	(-0.86)	(-1.54)	(-1.12)
CMA							0.12	0.11	0.06	0.05
							(1.23)	(1.15)	(0.65)	(0.49)
XRDF				0.00*		0.00**		0.00		0.00**
				(1.90)		(2.48)		(1.53)		(2.06)
Constant	0.28**	0.25**	0.31**	0.30**	0.22*	0.20*	0.32**	0.30**	0.25*	0.22*
	(2.29)	(2.05)	(2.48)	(2.37)	(1.84)	(1.76)	(2.41)	(2.25)	(1.86)	(1.75)
Obs (# of months)	552	552	552	552	552	552	552	552	552	552
R-squared	0.01	0.01	0.04	0.04	0.06	0.07	0.04	0.05	0.07	0.07

Table 9: Two-Way Portfolio Sorting on R&D Intensity

We conduct a sequential sort to examine the awarded-minus-unawarded (*AMU*) spread across different subgroups of R&D over the total asset ratio (R&D Intensity). By the end of fiscal year *t*-1, we identify awarded firms and their unawarded matched counterparts following the method that we used in Table 1. In both awarded and unawarded groups, firms with non-missing values of R&D intensities are further sorted into five subgroups based on quintiles (i.e., we separate firms into low (1), medium (2 to 4), and high (5) groups using the 20^{th} to the 80^{th} percentiles with 20-percentile increments) in year *t*-1. For each subgroup, we construct an awarded-minus-unawarded (*AMU*) portfolio by going long in the awarded portfolio and going short in the unawarded portfolio at June of year *t*, and allow the AMU portfolio to perform from July of year *t* to June of year *t*+1. We compute and compare the equal-weighted monthly returns for both the awarded portfolio and the unawarded portfolio. To test the statistical significance of abnormal returns adjusted for the exposure to risk factors, we regress the monthly returns in excess of the risk-free interest rate (*excess return*) and regress these excess returns on risk factors, such as the market factor (*MKT*) in the capital asset pricing model (*CAPM*), the size factor (*SMB*) and the value factor (*HML*) in the three-factor model (FF3) by Fama and French (1993), the momentum factor (*UMD*) in the four-factor model (*FF4*) by Carhart (1997), the profitability factor (*RMW*) and the investment factor (*CMA*) in the five-factor model (*FF5*) by Fama and French (2015). The Fama and French (2017) six-factor model (*FF6*) includes *MKT*, *SMB*, *HML*, *RMW*, *CMA*, and *UMD*. Numbers without parentheses report parameter estimates of excess return and their corresponding alphas, and numbers with parentheses show *t*-values. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively. All estimates are in percentage.

(Table 9 continued)

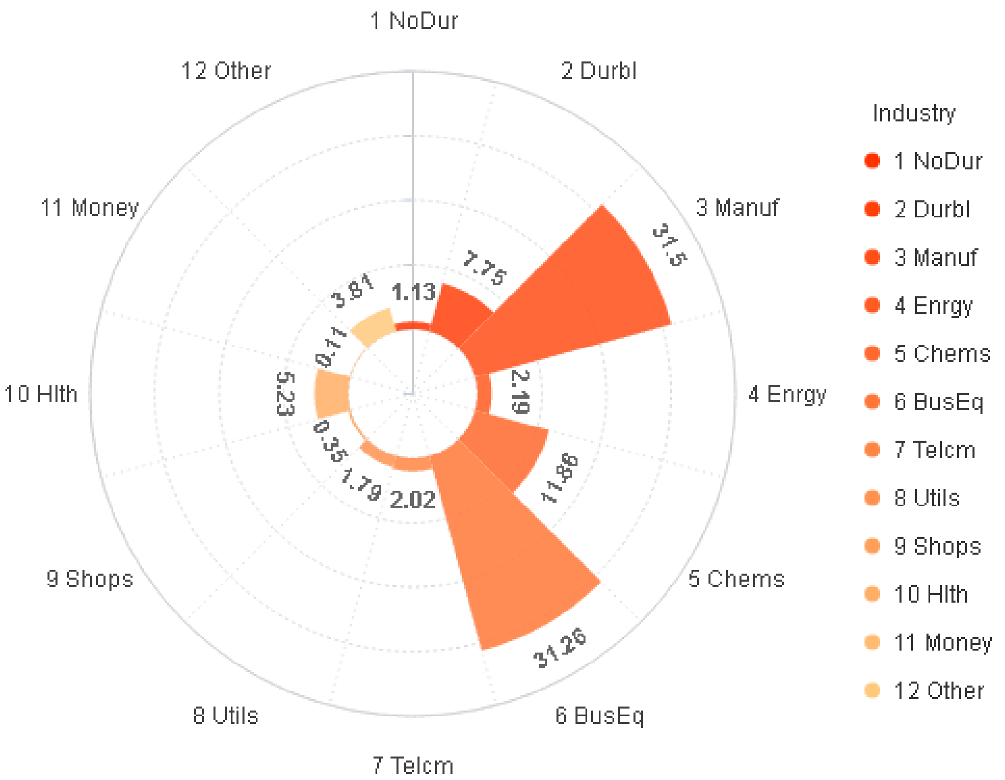
Award \ R&D Intensity		Low	High	High-Minus-Low
Unawarded		0.49	0.51	0.03
		(1.63)	(1.19)	(0.07)
Awarded		0.58*	1.53***	0.95*
		(1.95)	(2.84)	(1.87)
Awarded-Minus-Unawarded (AMU)				
Excess return	***Excess return***	0.09	1.01**	0.92*
		(0.45)	(2.34)	(1.91)
CAPM	***Alpha***	0.09	0.90**	0.81*
		(0.43)	(2.07)	(1.67)
FF3	***Alpha***	0.02	1.06**	1.04**
		(0.11)	(2.45)	(2.16)
FF4	***Alpha***	-0.10	0.75*	0.85*
		(-0.46)	(1.70)	(1.73)
FF5	***Alpha***	-0.01	1.30***	1.30***
		(-0.03)	(2.93)	(2.67)
FF6	***Alpha***	-0.11	1.02**	1.13**
		(-0.48)	(2.30)	(2.28)
FF3+XRDF	***Alpha***	0.03	1.01**	0.98**
		(0.12)	(2.34)	(2.06)
FF4+XRDF	***Alpha***	-0.10	0.64*	0.74*
		(-0.47)	(1.65)	(1.71)
FF5+XRDF	***Alpha***	-0.01	1.22***	1.22**
		(-0.04)	(2.76)	(2.51)
FF6+XRDF	***Alpha***	-0.11	0.89**	1.01**
		(-0.51)	(2.03)	(2.04)

Figures

Figure 1: Industry Distribution of Award Outcomes

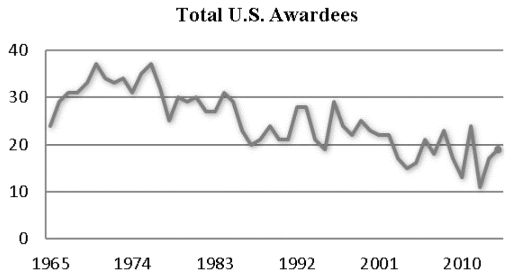
This figure reports the industry distribution and time-series variation of the award outcomes of the R&D 100 Award. The Fama-French 12 industries are defined in the following twelve categories: (1) Consumer Non-Durables (*NoDur*); (2) Consumer Durables (*Durbl*); (3) Manufacturing (*Manuf*); (4) Energy (*Enrgy*); (5) Chemicals (*Chems*); (6) Business Equipment (*BusEq*); (7) Telecom (*Telcm*); (8) Utilities (*Utils*); (9) Shops; (10) Health (*Hlth*); (11) Money; and (12) Other. The original sampling period ranges from 1965 to 2014. In Panel A, we exhibit the full-sample industry distribution of the award outcomes. The numbers imply the proportions (in percentages) of awards received by these industries. In Panel B, we separately display the time-series line charts of annual award outcomes of total U.S. awardees and Fama-French 12 industries. The vertical axis suggests the industry awarded share, for which the percentage is computed as the number of awarded firms in a specific industry divided by the total number of awarded firms in the same year.

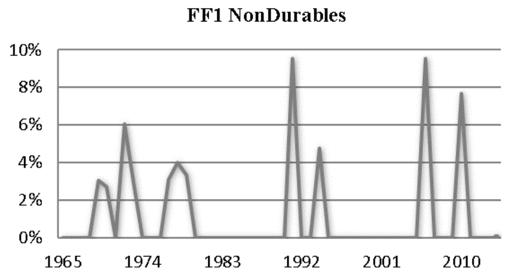
Panel A: Average Award Outcomes of FF12 Industries

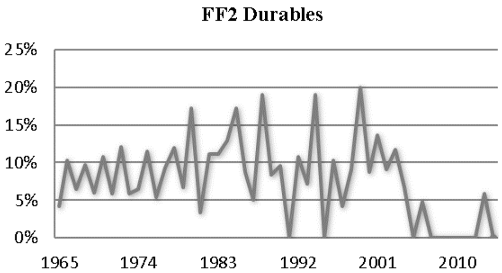


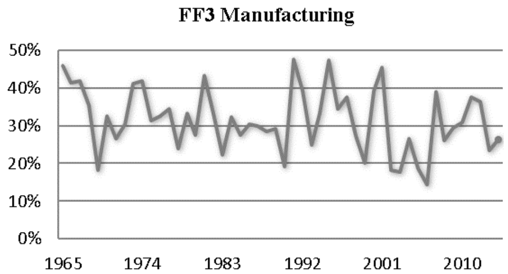
(Figure 1 continued)

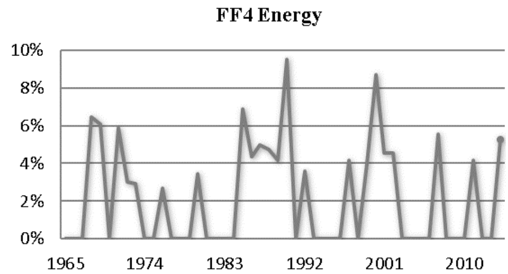
Panel B: Annual Award Outcomes: Time Series

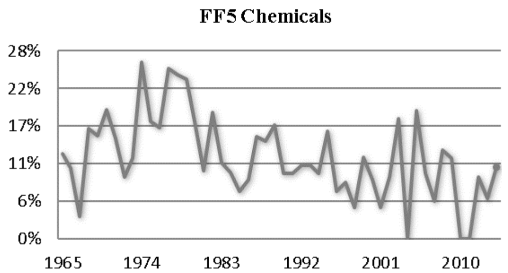


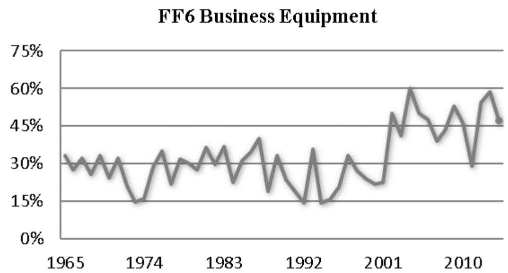


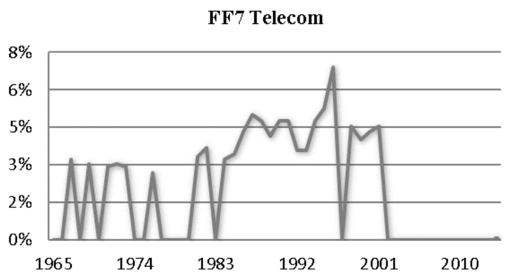


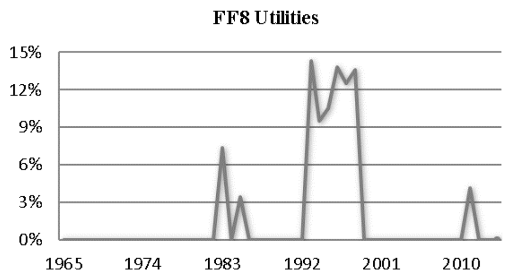












(Figure 1 continued)

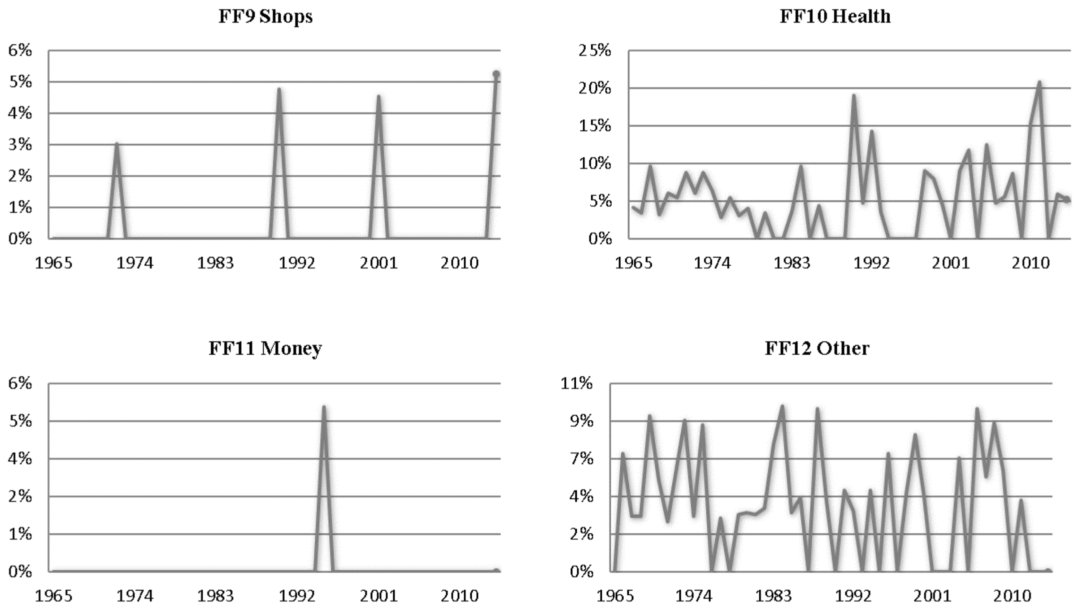


Figure 2: Performance of Long-Short Strategy along Sample Years

The black curve represents the total cumulative returns of our long-short strategy exploiting the awarded-minus-unawarded (*AMU*) spread in Table 4, starting from July 1970 to June 2016. The blue solid double curve plots the corresponding total cumulative abnormal returns of our long-short strategy backed out from the FF3 model. The cumulative return at month n is presented in percentages and defined as: $R_n = (1 + r_1) \cdot (1 + r_2) \cdot \cdots \cdot (1 + r_n)$. The overlay recession bands (shaded areas) correspond to the U.S. recession periods defined by the NBER.

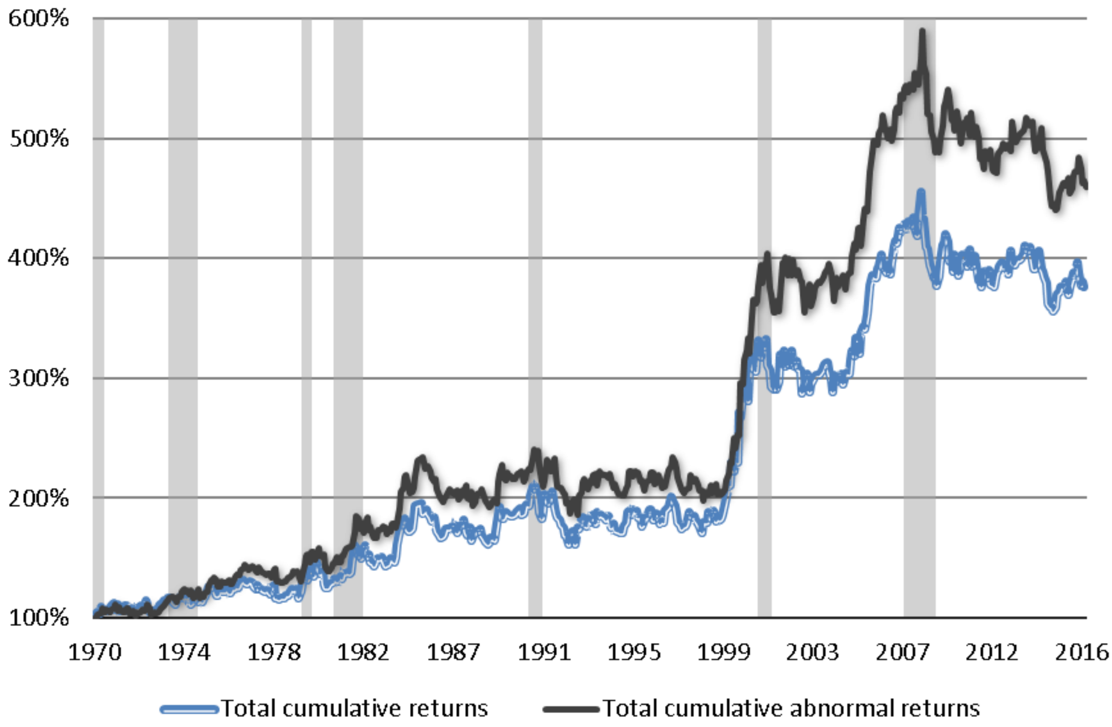


Figure 3: Five-year Cumulative Performance by Portfolio Month

The blue curve represents the total cumulative returns of the long-short strategy that longs the awarded portfolio and shorts the unawarded portfolio over a five-year horizon. The awarded and unawarded portfolios are constructed following the methodology that we used in Table 4. To trace the five-year performance of the long-short portfolio formed in June of year t+1, we set up the sequence from M1 to M60 to denote the portfolio month from July of year t+1 (one month after formation of the portfolios) to June of year t+6 (sixty months after formation of the portfolios). The total cumulative return in month n is defined as: $R_n = (1 + r_1) \cdot (1 + r_2) \cdot \cdots \cdot (1 + r_n)$ and is presented in percentages.

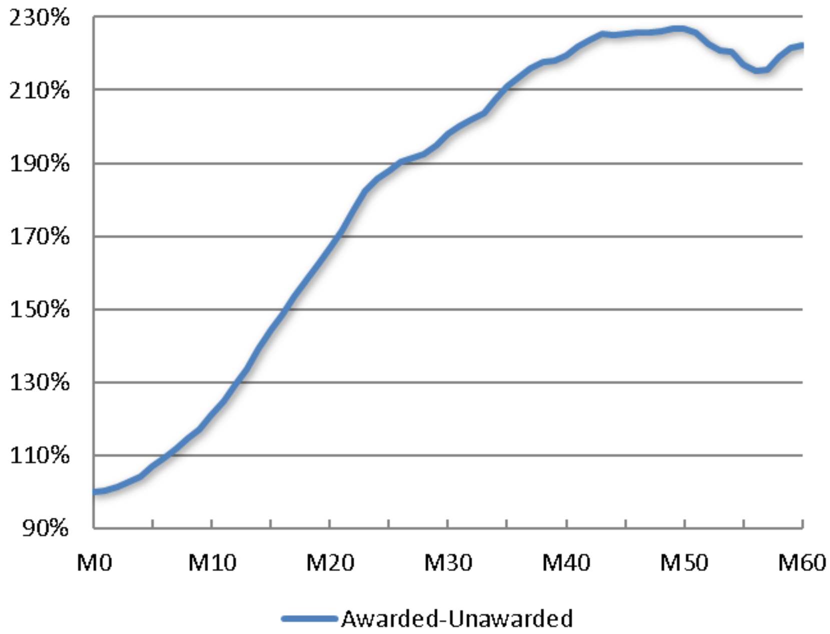


Figure 4: Future Five-year Market Beta

The red solid (green dotted) curve plots the future five-year market betas of awarded (unawarded) portfolios at each fiscal year end. The blue bar chart displays the difference between these two curves (awarded minus unawarded). The awarded and the unawarded portfolios are constructed following the methodology that we used in Table 4, and the future five-year market betas are estimated in Table 6. The vertical axis represents the parameter estimates of the future five-year market beta, while the horizontal axis shows the corresponding fiscal year.

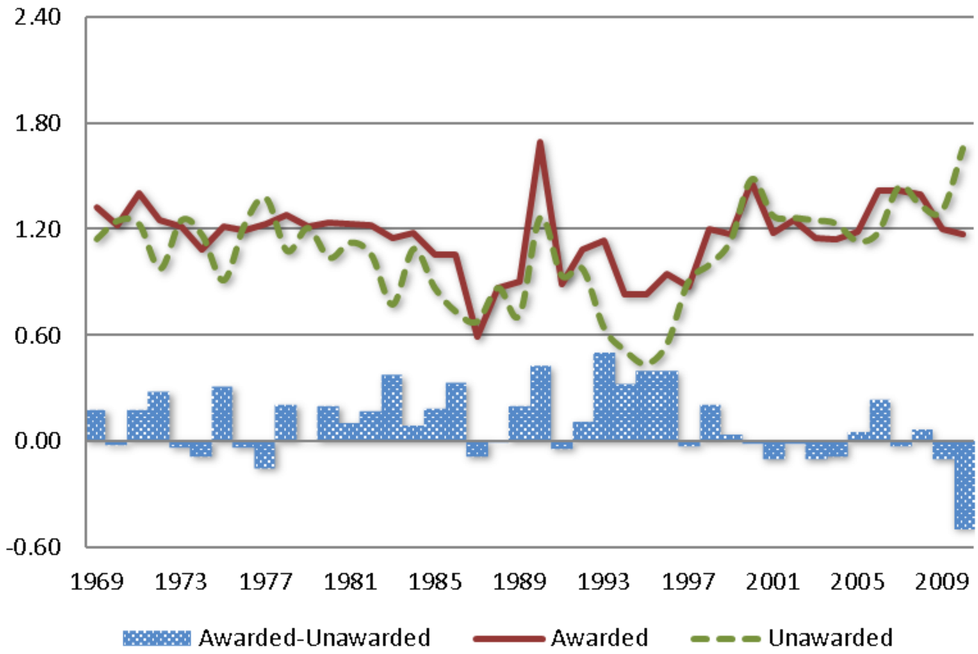
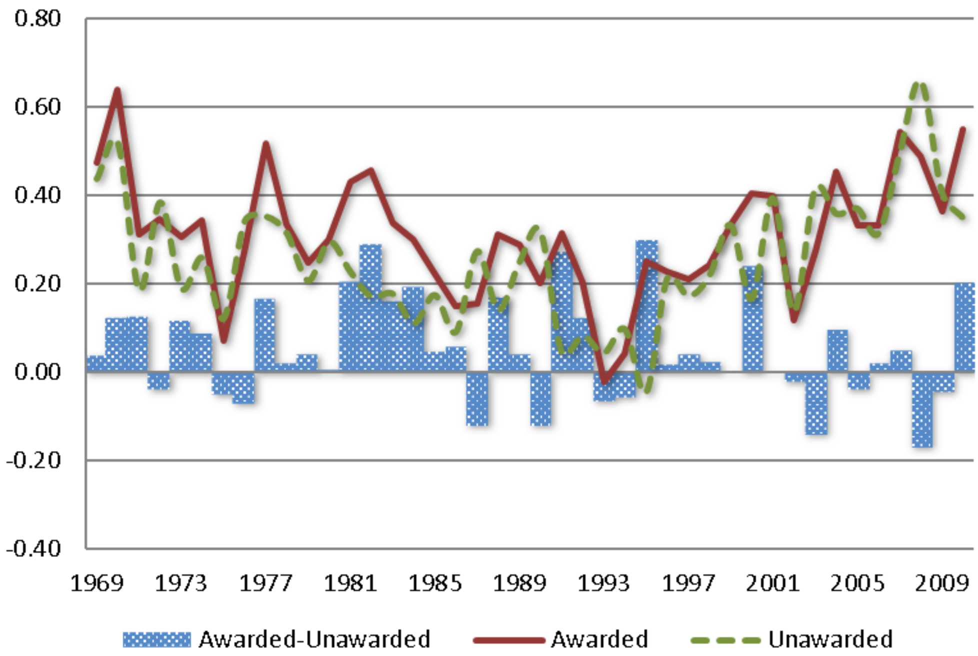


Figure 5: Future Five-year Procyclicality of Sales Growths

The red solid (green dotted) curve plots the future five-year procyclicality of sales growth of awarded (unawarded) portfolios at each fiscal year end. The blue bar chart displays the difference between these two curves (awarded minus unawarded). The awarded and the unawarded portfolios are constructed following the methodology that we used in Table 4, and the future five-year procyclicality of sales growth is estimated in Table 7. The vertical axis represents the parameter estimates of the future five-year procyclicality of sales growth, while the horizontal axis shows the corresponding fiscal year.



Online Appendix of

Innovation Awards, Product Segmentation, and Stock Returns

Online Appendix: Model

We develop a two-product model that endogenizes the probabilistic award outcome, R&D investment, and product market performance and offers asset pricing implications of the R&D 100 Awards from the perspective of consumption in segmented product markets.

1. Model setup

Consumption products. A representative agent with an infinite life consumes two types of products at time *t*: the consumption of the low-end product is denoted as C_t, and the consumption of the high-end product is denoted as H_t. Following Ait-Sahalia et al. (2004), the utility function is an additive form of the direct utility of the low-end product and that of the high-end product:

$$U\left(C_t, H_t\right) = u\left(C_t\right) + v\left(H_t\right),$$

where the direct utility functions of both products take the forms of constant relative risk aversion:

$$u\left(C_t\right) = \frac{C_t^{1-\varphi}}{1-\varphi}, \text{ and} \tag{1}$$

$$v\left(H_t\right) = \frac{H_t^{1-\psi}}{1-\psi}. \tag{2}$$

Following the logic of Ait-Sahalia et al. (2004), we assume that the intertemporal elasticity of substitution of the low-end product is smaller than that of the high-end product (i.e., $\varphi > \psi > 1$).[1]

The representative agent decides the amounts of the low-end and the high-end

[1] Technically, this assumption implies that, as wealth goes to infinity, the budget share of the high-end product goes to one. We are different from Ait-Sahalia et al. (2004) in that, while they focus on the basic and luxury goods, which respectively target on consumers with different levels of wealth, we study the demands for low-end and high-end goods as technology evolves.

products to consume and the amount of financial investment. The optimization problem of the representative agent can be written as:

$$J_t\left(W_t\right)=\max_{\{C_t,H_t,\omega_t\}}\left\{u\left(C_t\right)+v\left(H_t\right)+E_t\left[\beta J_{t+1}\left(W_{t+1}\right)\right]\right\}, \tag{3}$$

$$\text{s.t. } W_{t+1}=\left(W_t-C_t-P_tH_t\right)\left(\omega_t\left(r_{m,t+1}-r_{f,t+1}\right)+r_{f,t+1}\right),$$

where W_t is the wealth at time t, ω_t is the proportion of wealth invested in the market portfolio at time t, $J_t(W_t)$ is the value function given the wealth at time t, $r_{m,t+1}$ is the return of the market portfolio at time t+1, $r_{f,t+1}$ is the risk-free return at time t+1, and β is the subjective discount factor. It is noteworthy that $P_t > 0$ is the price premium of the high-end product relative to the low-end product.

The Euler equations of the representative agent's optimization problem can be written in the following three equations:

$$u'\left(C_t\right)-\beta E_t\left[J'_{t+1}\left(W_{t+1}\right)\left(\omega_t\left(r_{m,t+1}-r_{f,t+1}\right)+r_{f,t+1}\right)\right]=0, \tag{4}$$

$$v'\left(H_t\right)-\beta P_tE_t\left[J'_{t+1}\left(W_{t+1}\right)\left(\omega_t\left(r_{m,t+1}-r_{f,t+1}\right)+r_{f,t+1}\right)\right]=0, \text{ and} \tag{5}$$

$$E_t\left[J'_{t+1}\left(W_{t+1}\right)\left(W_t-C_t-P_tH_t\right)\left(r_{m,t+1}-r_{f,t+1}\right)\right]=0. \tag{6}$$

In order to solve the model in close form, we follow the modelling of an endowment economy (e.g., Mehra and Prescott (1985)) and assume that the supply of the low-end product is given by a process following a logarithm drifted random walk[2]:

$$\ln C_{t+1}=\ln C_t+\mu+\sigma\varepsilon_{t+1}, \tag{7}$$

where $\varepsilon_{t+1}\sim N(0,1)$ is the aggregate consumption shock at time t+1 conditional on the information at time t, $\mu > 0$ is the parameter of the drift term, and $\sigma > 0$ is the parameter of the variance term. Besides, we follow the argument of Ait-Sahalia et al. (2004) and assume that the price premium of the high-end good is procyclical:

$$P_t=\eta C_t^{\lambda}, \tag{8}$$

or

$$\ln P_{t+1}=\ln P_t+\lambda\mu+\lambda\sigma\varepsilon_{t+1}, \tag{9}$$

[2] The only driver of our cross-sectional asset pricing implications is the different dynamics of the two product markets instead of the specific form of the time-series variation of consumption.

where η and λ are two positive parameters.

Inserting Equations (1), (2), and (8) into Equations (4) and (5) yields the process of demand for the high-end good:

$$P_t H_t = \rho C_t^{\theta}, \tag{10}$$

where $\rho \equiv \eta^{\frac{\psi-1}{\psi}} > 0$ and $\theta \equiv \frac{\varphi}{\psi} + \lambda\left(1 - \frac{1}{\psi}\right) > 1$. Such derivation is contained in the section "Additional Derivations". Equation (10) implies the following Lemma 1.

Lemma 1 The procyclicality of the high-end product is higher than that of the low-end product.

With Equation (10), we point out that the excess procyclicality of the high-end product (i.e., θ) comes from two sources: first, the weaker incentive of consumption smoothing for the high-end good (i.e., $\varphi/\psi > 1$), and second, the procyclicality of the high-end good's price premium (i.e., $\lambda(1 - 1/\psi) > 0$). It is noteworthy that Lemma 1 still holds when we rule out the time variation of the high-end good's price premium (i.e., $\lambda = 0$).

Applying the envelope theorem to Equation (3), we can derive:

$$J_t'\left(W_t^*\right) = u'\left(C_t\right) = v'\left(H_t\right)/P_t. \tag{11}$$

Substituting Equation (11) into Equation (4) yields:

$$E_t\left[\beta \frac{u'\left(C_{t+1}\right)}{u'\left(C_t\right)} r_{f,t+1}\right] = 1. \tag{12}$$

On the other hand, substituting Equation (11) into Equation (5) yields:

$$E_t\left[\beta \frac{v'\left(H_{t+1}\right)/P_{t+1}}{v'\left(H_t\right)/P_t} r_{f,t+1}\right] = 1. \tag{13}$$

Therefore, Equations (12) and (13) collectively solve the process of stochastic discount factor:

$$\frac{M_{t+1}}{M_t} = \frac{\beta u'\left(C_{t+1}\right)}{u'\left(C_t\right)} = \frac{\beta v'\left(H_{t+1}\right)P_t}{v'\left(H_t\right)P_{t+1}} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\varphi},$$

or

$$\ln M_{t+1} = \ln M_t - \gamma - \kappa \varepsilon_{t+1}, \tag{14}$$

where $\gamma \equiv \varphi\mu - \ln\beta > 0$ and $\kappa \equiv \varphi\sigma > 0$.

Firm's behavior in product markets. We consider that one firm operates in three periods, τ, τ+1, and τ+2, in the economy. Its stochastic sales (F_S) in each period is given by the following equation:

$$F_s = \xi C_s + D_s \cdot n\xi P_s H_s,$$

where s takes the value of τ, τ+1, or τ+2. For simplicity's sake, we normalize operating costs as zero, and thus sales equals profits. The parameter ξ measures the share of the product markets that the focal firm takes, and the parameter n captures the number of growth opportunities (e.g., talents, initial market positions, and brand images) in the high-end product market for the firm. We assume that the focal firm can capitalize the high-end product market only if it is recognized by the R&D 100 Award. Therefore, D_S takes the value of zero when the firm is not awarded and takes the value of one when it is awarded.

At Date τ, the firm maximizes its firm value and invests a lump-sum R&D investment, I, to develop innovative products; consequently, the firm has a probability to be awarded, π, at Date τ+1. We assume that the probability of receiving the award is increasing in the R&D investment (i.e., $\partial\pi/\partial I > 0$), but the marginal benefit of R&D investment diminishes (i.e., $\partial^2\pi/\partial I^2 < 0$).[3]

2. Firm's optimal strategy and comparative statics

To derive the optimal investment, I, at Date τ, we solve the firm value in backward induction. The value of an unawarded firm at Date τ+1 is:

$$V_{\tau+1}^{U} = E_{\tau+1}\left[\frac{M_{\tau+2}}{M_{\tau+1}}\left(\xi C_{\tau+2}\right)\right], \tag{15}$$

and the value of an awarded firm at Date τ+1 is:

[3] We run Logistic and Probit regressions with a sample of all public firms and support the positive relation between R&D investment and awarding probability in our Online Appendix Table OA4.

$$V_{\tau+1}^{A}=E_{\tau+1}\left[\frac{M_{\tau+2}}{M_{\tau+1}}\left(\xi C_{\tau+2}+n\xi pH_{\tau+2}\right)\right]. \tag{16}$$

The maximization problem of the firm at Date τ is given below:

$$\max_{I}\left\{\xi C_{\tau}-I+E_{\tau}\left[\frac{M_{\tau+1}}{M_{\tau}}\left(\xi C_{\tau+1}+\pi V_{\tau+1}^{A}+\left(1-\pi\right)V_{\tau+1}^{U}\right)\right]\right\}.$$

Re-arranging the maximization problem with Equations (15) and (16), the first-order condition can be derived in the following equation:

$$\frac{\partial\pi}{\partial I}E_{\tau}\left[\frac{M_{\tau+2}}{M_{\tau}}n\xi P_{\tau+2}H_{\tau+2}\right]=1. \tag{17}$$

This first-order condition in Equation (17) implies that the firm will invest so that the marginal benefit of R&D investments, which is calculated as the increment of award probability multiplied by the present value of the increased firm value, equals the marginal cost of investment, which is assumed to be one and constant. Taking the derivative with respect to n on both sides of Equation (17), we can derive the following inequality: $\partial^2\pi/(\partial I\partial n)<0$. Following the chain rule of derivatives, we obtain:

$$\frac{\partial I^{*}}{\partial n}=\frac{\partial^{2}\pi}{\partial I^{*}\partial n}\bigg/\frac{\partial^{2}\pi}{\partial I^{*2}}>0, \tag{18}$$

which leads to the following Lemma 2.

Lemma 2 The firm's R&D investments increase with the number of growth opportunities in the high-end product market (i.e., $\partial I^*/\partial n>0$).

The mechanism of Lemma 2 is that, given the probability of being awarded, the present value of being awarded (i.e., $E_\tau[(M_{\tau+2}/M_\tau)n\xi P_{\tau+2}H_{\tau+2}]$) is higher when the number of growth opportunities in the high-end market (i.e., n) is larger; therefore, the firm with more growth opportunities invests more in R&D at the first place. Lemma 2 connects growth opportunities to firms' R&D choices and is related to previous studies that document the relation between R&D investments and growth opportunities, such as Berk et al. (1999), Carlson et al. (2004), Li (2011), Garleanu et al. (2012), Lin (2012), and Ai and Kiku (2013), among others.

The firm value net of dividend and R&D investment at Date τ can be expressed as:

$$V_{\tau}=E_{\tau}\left[\frac{M_{\tau+1}}{M_{\tau}}\left(\xi C_{\tau+1}+\pi V_{\tau+1}^{A}+(1-\pi)V_{\tau+1}^{U}\right)\right], \tag{19}$$

and the expected stock return at Date τ is given by the following equation:

$$E_{\tau}\left[r_{\tau+1}\right]\equiv\frac{E_{\tau}\left[\xi C_{\tau+1}+\pi V_{\tau+1}^{A}+(1-\pi)V_{\tau+1}^{U}\right]}{V_{\tau}}. \tag{20}$$

Re-organizing Equation (20) with Equations (7)-(10), (14)-(16), and (19), we can show that $E_{\tau}[r_{\tau+1}]$ increases in n (i.e., $\partial E_{\tau}[r_{\tau+1}]/\partial n>0$). Therefore, we obtain the following inequality and Lemma 3, following the chain rule of derivatives:

$$\frac{\partial E_{\tau}\left[r_{\tau+1}\right]}{\partial I^{*}}=\frac{\partial E_{\tau}\left[r_{\tau+1}\right]}{\partial n}\bigg/\frac{\partial I^{*}}{\partial n}>0.$$

Lemma 3 The expected stock return of the firm increases with its ex-ante R&D investment (i.e., $\partial E_{\tau}[r_{\tau+1}]/\partial I^{*}>0$).

Lemma 3 is true under the condition that $\varphi>\psi$. It points out a mechanism of the positive relation between R&D investments and expected stock return: a firm with higher R&D investments is the one with more growth opportunities and larger exposure to aggregate consumption risks and therefore generates higher expected stock return. Hence, Lemma 3 is consistent with the empirical finding that R&D expenditure is a positive return predictor (see Lev and Sougiannis (1996), Deng et al. (1999), and Chan et al. (2001)).

Next, we turn to the discussion on the effect of being awarded on stock returns. The stock returns of an unawarded firm and an awarded firm at Date τ+2 are given as:

$$r_{\tau+2}^{U}=\frac{\xi C_{\tau+2}}{V_{\tau+1}^{U}},\ \text{and} \tag{21}$$

$$r_{\tau+2}^{A}=\frac{\xi C_{\tau+2}+n\xi P_{\tau+2}H_{\tau+2}}{V_{\tau+1}^{A}}, \tag{22}$$

respectively. Therefore, with Equations (7)-(10) and (15)-(16), the expected stock returns of an unawarded firm and an awarded firm at Date τ+1 can be derived as:

$$E_{\tau+1}\left[r_{\tau+2}^{U}\right]=\exp\left\{\gamma+\sigma\kappa-\frac{1}{2}\kappa^{2}\right\}, \text{ and} \tag{23}$$

$$E_{\tau+1}\left[r_{\tau+2}^{A}\right]=E_{\tau+1}\left[r_{\tau+2}^{U}\right]\cdot\left[1+\frac{\Psi\left(n,C_{\tau+1}\right)}{1+\Psi\left(n,C_{\tau+1}\right)}\left(\exp\left\{(\theta-1)\sigma\kappa\right\}-1\right)\right], \tag{24}$$

respectively, where $\Psi(n, C_{\tau+1})$ is defined as the following increasing function of both n and $C_{\tau+1}$:

$$\Psi\left(n,C_{\tau+1}\right)\equiv n\rho C_{\tau+1}^{\theta-1}\exp\left\{(\theta-1)(\mu-\sigma\kappa)+\frac{1}{2}\left(\theta^{2}-1\right)\sigma^{2}\right\}>0. \tag{25}$$

We derive Equations (23)-(25) in details in the section "Additional Derivations".

From Equations (23) and (24), we can derive that the awarded-minus-unawarded return spread (r_{AMU}), which is the difference between the expected stock return of an awarded firm ($E_{\tau+1}[r_{\tau+2}^{A}]$) and the expected stock return of an unawarded firm ($E_{\tau+1}[r_{\tau+2}^{U}]$) (also known as the risk premium of an awarded firm):

$$r_{AMU}\equiv E_{\tau+1}\left[r_{\tau+2}^{A}-r_{\tau+2}^{U}\right]=E_{\tau+1}\left[r_{\tau+2}^{U}\right]\cdot\frac{\Psi\left(n,C_{\tau+1}\right)}{1+\Psi\left(n,C_{\tau+1}\right)}\left(e^{(\theta-1)\sigma\kappa}-1\right)>0 \tag{26}$$

Inequality (26) leads to Proposition 1.

Proposition 1 The expected stock return of an awarded firm is higher than that of an unawarded firm, i.e., $r_{AMU} > 0$.

Following the asset pricing literature (e.g., Berk et al. (1999) and Zhang (2005), among others), we define a firm's exposure to systematic consumption risk as the inverse of the ratio of its covariance between the log return and the log stochastic discount factor over the variance of the log discount factor. Therefore, we can derive the systematic risk exposures of an unawarded firm and an awarded firm in the following two equations, respectively:

$$\beta_{U}=-\frac{Cov_{\tau+1}\left[\ln\left(\frac{M_{\tau+2}}{M_{\tau+1}}\right),\ln r_{\tau+2}^{U}\right]}{Var_{\tau+1}\left[\ln\left(\frac{M_{\tau+2}}{M_{\tau+1}}\right)\right]}, \text{ and} \tag{27}$$

$$\beta_A = -\frac{Cov_{\tau+1}\left[\ln\left(\frac{M_{\tau+2}}{M_{\tau+1}}\right), \ln r_{\tau+2}^{A}\right]}{Var_{\tau+1}\left[\ln\left(\frac{M_{\tau+2}}{M_{\tau+1}}\right)\right]}. \tag{28}$$

respectively. Because $\theta > 1$, we prove in the section "Additional Derivations" that

$$\beta_A > \beta_U, \tag{29}$$

and the following proposition.

Proposition 2 The systematic risk exposure of an awarded firm is higher than that of an unawarded firm (i.e., $\beta_A > \beta_U$).

As the profit from the high-end product market is more procyclical than that from the low-end product market (Lemma 1), an awarded firm, which capitalizes growth opportunities in the high-end market, has a higher exposure to consumption risks. Therefore, Propositions 1 and 2 collectively imply that an awarded firm is riskier than an unawarded firm and thus requires a higher expected stock return.[4]

As both the low-end and the high-end product markets generate profits procyclical to aggregate consumption but to different degrees, the risk premium of an awarded firm naturally comoves with aggregate consumption. As $\Psi(n, C_{\tau+1})$ is an increasing function of $C_{\tau+1}$ in Equation (25), the partial derivative of r_{AMU} with respect to $C_{\tau+1}$ is positive:

$$\frac{\partial r_{AMU}}{\partial C_{\tau+1}} > 0.$$

Such inequality leads to Proposition 3.

Proposition 3 The risk premium of an awarded firm is procyclical to aggregate consumption (i.e., $\partial r_{AMU}/\partial C_{\tau+1} > 0$).

When the aggregate consumption follows a logarithm drifted random walk in Equation (7), the expected growth rate and volatility of consumption are higher if the

[4] Previous literature, such as Berk et al. (1999), Carlson et al. (2004), Aguerrevere (2009), and Garleanu et al. (2012), among others, has documented that growth options are riskier than assets in place.

current consumption is higher. Therefore, an awarded firm, which has a higher exposure to the aggregate consumption risks (Proposition 2), should demand a higher risk premium in periods of higher consumption.

We can also connect the risk premium of an awarded firm with ex-ante R&D investment. Since $\Psi(n, C_{\tau+1})$ is an increasing function of n (Equation (25)), we can derive that $\partial r_{AMU}/\partial n > 0$. Therefore, combining this inequality with (18) and applying the chain rule of derivative, we can obtain:

$$\frac{\partial r_{AMU}}{\partial I^*} = \frac{\partial r_{AMU}}{\partial n} \bigg/ \frac{\partial I^*}{\partial n} > 0,$$

and the following Proposition 4.

Proposition 4 The risk premium of an awarded firm is higher when the firm's ex-ante R&D investment is higher (i.e., $\partial r_{AMU}/\partial I^* > 0$).

Since the ex-ante intensity of R&D investment increases with the number of growth opportunities (Lemma 2), the award capitalizes more growth opportunities and brings higher additional systematic risks for an awarded firm with higher ex-ante R&D investment. Therefore, the risk premium of an awarded firm is higher when its ex-ante R&D investment is higher.

3. Additional Derivations

***Derivation of Equation* (10).** From Equation (11), we have:

$$u'(C_t) = v'(H_t)/P_t.$$

We use Equations (1), (2), and (8) and derive the above equation in the following explicit form:

$$H_t = \eta^{-\frac{1}{\psi}} C_t^{\frac{\varphi-\lambda}{\psi}},$$

or

$$P_t H_t = \rho C_t^{\theta},$$

where $\rho \equiv \eta^{\frac{\psi-1}{\psi}} > 0$ and $\theta \equiv \frac{\varphi}{\psi} + \lambda\left(1 - \frac{1}{\psi}\right)$.

***Derivation of Equations* (23)-(25).** From Equations (15) and (16), we derive $V_{\tau+1}^{U}$ and $V_{\tau+1}^{A}$ in the following explicit forms:

$$
\begin{aligned}
V_{\tau+1}^{U} &= E_{\tau+1}\left[\frac{M_{\tau+2}}{M_{\tau+1}}\left(\xi C_{\tau+2}\right)\right] \\
&= \xi C_{\tau+1} E_{\tau+1}\left[\exp\left\{\left(\mu-\gamma\right)+\left(\sigma-\kappa\right)\varepsilon_{\tau+2}\right\}\right] \\
&= \xi C_{\tau+1} \exp\left\{\left(\mu-\gamma\right)+\frac{1}{2}\left(\sigma-\kappa\right)^{2}\right\},
\end{aligned}
$$

and

$$
\begin{aligned}
V_{\tau+1}^{A} &= E_{\tau+1}\left[\frac{M_{\tau+2}}{M_{\tau+1}}\left(\xi C_{\tau+2} + n\xi P_{\tau+2} H_{\tau+2}\right)\right] \\
&= \xi C_{\tau+1} E_{\tau+1}\left[\exp\left\{\left(\mu-\gamma\right)+\left(\sigma-\kappa\right)\varepsilon_{\tau+2}\right\}\right] + n\xi\rho C_{\tau+1}^{\theta} E_{\tau+1}\left[\exp\left\{\left(\theta\mu-\gamma\right)+\left(\theta\sigma-\kappa\right)\varepsilon_{\tau+2}\right\}\right] \\
&= \xi C_{\tau+1} \exp\left\{\left(\mu-\gamma\right)+\frac{1}{2}\left(\sigma-\kappa\right)^{2}\right\} + n\xi\rho C_{\tau+1}^{\theta} \exp\left\{\left(\theta\mu-\gamma\right)+\frac{1}{2}\left(\theta\sigma-\kappa\right)^{2}\right\}.
\end{aligned}
$$

Thus, from Equations (21) and (22), we derive $r_{\tau+2}^{U}$ and $r_{\tau+2}^{A}$ in the following explicit forms:

$$
\begin{aligned}
r_{\tau+2}^{U} &= \frac{\xi C_{\tau+2}}{V_{\tau+1}^{U}} \\
&= \frac{\xi C_{\tau+1} \exp\left\{\mu+\sigma\varepsilon_{\tau+2}\right\}}{\xi C_{\tau+1} \exp\left\{\left(\mu-\gamma\right)+\frac{1}{2}\left(\sigma-\kappa\right)^{2}\right\}} \\
&= \exp\left\{\gamma-\frac{1}{2}\left(\sigma-\kappa\right)^{2}+\sigma\varepsilon_{\tau+2}\right\},
\end{aligned}
$$

and

$$
\begin{aligned}
r_{\tau+2}^{A} &= \frac{\xi C_{\tau+2} + n\xi P_{\tau+2} H_{\tau+2}}{V_{\tau+1}^{A}} \\
&= \frac{\xi C_{\tau+1} E_{\tau+1}\left[\exp\left\{\mu+\sigma\varepsilon_{\tau+2}\right\}\right] + n\xi\rho C_{\tau+1}^{\theta} E_{\tau+1}\left[\exp\left\{\theta\mu+\theta\sigma\varepsilon_{\tau+2}\right\}\right]}{\xi C_{\tau+1} \exp\left\{\left(\mu-\gamma\right)+\frac{1}{2}\left(\sigma-\kappa\right)^{2}\right\} + n\xi\rho C_{\tau+1}^{\theta} \exp\left\{\left(\theta\mu-\gamma\right)+\frac{1}{2}\left(\theta\sigma-\kappa\right)^{2}\right\}}.
\end{aligned}
$$

Therefore, the expectations of $r_{\tau+2}^{U}$ and $r_{\tau+2}^{A}$ can be expressed as follows:

$$
E_{\tau+1}\left[r_{\tau+2}^{U}\right] = \exp\left\{\gamma+\sigma\kappa-\frac{1}{2}\kappa^{2}\right\}, \quad \text{and}
$$

$$E_{\tau+1}\left[r_{\tau+2}^{A}\right]=\frac{\xi C_{\tau+1}E_{\tau+1}\left[\exp\left\{\mu+\frac{1}{2}\sigma^{2}\right\}\right]+n\xi\rho C_{\tau+1}^{\theta}E_{\tau+1}\left[\exp\left\{\theta\mu+\frac{1}{2}\theta^{2}\sigma^{2}\right\}\right]}{\xi C_{\tau+1}\exp\left\{(\mu-\gamma)+\frac{1}{2}(\sigma-\kappa)^{2}\right\}+n\xi\rho C_{\tau+1}^{\theta}\exp\left\{(\theta\mu-\gamma)+\frac{1}{2}(\theta\sigma-\kappa)^{2}\right\}}.$$

If we define an intermediate variable, $\Psi(n, C_{\tau+1})$, as a function of both n and $C_{\tau+1}$, we have:

$$\Psi\left(n,C_{\tau+1}\right)\equiv n\rho C_{\tau+1}^{\theta-1}\exp\left\{(\theta-1)(\mu-\sigma\kappa)+\frac{1}{2}\left(\theta^{2}-1\right)\sigma^{2}\right\},$$

then the expectation of $r_{\tau+2}^{A}$ can be simplified as follows:

$$E_{\tau+1}\left[r_{\tau+2}^{A}\right]=E_{\tau+1}\left[r_{\tau+2}^{U}\right]\cdot\left[1+\frac{\Psi\left(n,C_{\tau+1}\right)}{1+\Psi\left(n,C_{\tau+1}\right)}\left(\exp\left\{(\theta-1)\sigma\kappa\right\}-1\right)\right].$$

***Proof of Inequality* (29).** From Equations (27) and (28), the expressions of β_U and β_A can be simplified as follows:

$$\begin{aligned}\beta_{U}&=-\frac{Cov_{\tau+1}\left[\ln\left(\frac{M_{\tau+2}}{M_{\tau+1}}\right),\ln r_{\tau+2}^{U}\right]}{Var_{\tau+1}\left[\ln\left(\frac{M_{\tau+2}}{M_{\tau+1}}\right)\right]}\\&=-\frac{Cov_{\tau+1}\left[-\gamma-\kappa\varepsilon_{\tau+2},\gamma-\frac{1}{2}(\sigma-\kappa)^{2}+\sigma\varepsilon_{\tau+2}\right]}{Var_{\tau+1}\left[-\gamma-\kappa\varepsilon_{\tau+2}\right]}\\&=\frac{Cov_{\tau+1}\left[\kappa\varepsilon_{\tau+2},\sigma\varepsilon_{\tau+2}\right]}{Var_{\tau+1}\left[\kappa\varepsilon_{\tau+2}\right]}=\frac{\sigma}{\kappa},\end{aligned}$$

and

$$\beta_A = -\frac{Cov_{\tau+1}\left[\ln\left(\frac{M_{\tau+2}}{M_{\tau+1}}\right), \ln r_{\tau+2}^{A}\right]}{Var_{\tau+1}\left[\ln\left(\frac{M_{\tau+2}}{M_{\tau+1}}\right)\right]}$$

$$= \frac{Cov_{\tau+1}\left[\kappa\varepsilon_{\tau+2}, \ln\left(\xi C_{\tau+1}\exp\left\{\mu+\sigma\varepsilon_{\tau+2}\right\} + n\xi\rho C_{\tau+1}^{\theta}\exp\left\{\theta\mu+\theta\sigma\varepsilon_{\tau+2}\right\}\right)\right]}{Var_{\tau+1}\left[\kappa\varepsilon_{\tau+2}\right]}$$

$$> \frac{Cov_{\tau+1}\left[\kappa\varepsilon_{\tau+2}, \ln\left(n\xi\rho C_{\tau+1}^{\theta}\exp\left\{\theta\mu+\theta\sigma\varepsilon_{\tau+2}\right\}\right)\right]}{Var_{\tau+1}\left[\kappa\varepsilon_{\tau+2}\right]}$$

$$= \frac{Cov_{\tau+1}\left[\kappa\varepsilon_{\tau+2}, \theta\sigma\varepsilon_{\tau+2}\right]}{Var_{\tau+1}\left[\kappa\varepsilon_{\tau+2}\right]}$$

$$= \theta\frac{\sigma}{\kappa} > \frac{\sigma}{\kappa}.$$

The inequality holds because $\theta > 1$.

Online Appendix: Tables

Table OA1: One-Way Portfolio Sorting with Unawarded Benchmarks

This table supplements Table 4 by reporting the excess returns and corresponding alphas and betas of the awarded portfolio, unawarded portfolio, and the awarded-minus-unawarded (*AMU*) portfolio under all factor models. Numbers without parentheses report parameter estimate of excess returns, alphas, and betas, and numbers with parentheses show *t*-values. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively. All estimates are in percentage.

Models	Variables	Awarded	Unawarded	Awarded-Minus-Unawarded
Excess return	***Excess return***	0.93***	0.65**	0.28**
		(3.54)	(2.49)	(2.30)
CAPM	***Alpha***	0.25*	0.00	0.25**
		(1.92)	(0.00)	(2.03)
	MKT	1.19***	1.13***	0.06**
		(41.82)	(35.88)	(2.09)
FF3	***Alpha***	0.15	-0.17	0.32**
		(1.41)	(-1.46)	(2.57)
	MKT	1.10***	1.06***	0.04
		(45.27)	(40.04)	(1.57)
	SMB	0.61***	0.69***	-0.07*
		(17.48)	(18.05)	(-1.80)
	HML	0.07**	0.21***	-0.14***
		(1.98)	(5.19)	(-3.13)
FF4	***Alpha***	0.21*	-0.02	0.23*
		(1.93)	(-0.19)	(1.84)
	MKT	1.09***	1.02***	0.06**
		(44.04)	(39.30)	(2.25)
	SMB	0.61***	0.68***	-0.07*
		(17.52)	(18.55)	(-1.75)
	HML	0.05	0.15***	-0.10**
		(1.33)	(3.79)	(-2.29)
	UMD	-0.06***	-0.16***	0.10***
		(-2.66)	(-6.31)	(3.43)

(Table OA1 continued)

Models	Variables	Awarded	Unawarded	Awarded-Minus-Unawarded
FF5	*Alpha*	0.13	-0.19	0.32**
		(1.23)	(-1.63)	(2.56)
	MKT	1.12***	1.07***	0.05
		(43.35)	(37.92)	(1.60)
	SMB	0.59***	0.69***	-0.10**
		(15.89)	(17.02)	(-2.32)
	HML	-0.01	0.17***	-0.18***
		(-0.16)	(3.18)	(-3.09)
	RMW	-0.07	0.02	-0.09
		(-1.51)	(0.33)	(-1.59)
	CMA	0.19**	0.08	0.11
		(2.57)	(0.99)	(1.27)
FF6	*Alpha*	0.18*	-0.07	0.26**
		(1.70)	(-0.62)	(2.01)
	MKT	1.10***	1.04***	0.06**
		(42.93)	(38.21)	(2.04)
	SMB	0.59***	0.69***	-0.10**
		(16.03)	(17.72)	(-2.37)
	HML	-0.05	0.07	-0.12**
		(-1.04)	(1.22)	(-1.99)
	UMD	-0.07***	-0.17***	0.10***
		(-3.06)	(-6.66)	(3.42)
	RMW	-0.06	0.05	-0.11*
		(-1.19)	(1.04)	(-1.96)
	CMA	0.24***	0.18**	0.06
		(3.10)	(2.21)	(0.65)
FF3+XRDF	*Alpha*	0.13	-0.18	0.30**
		(1.24)	(-1.54)	(2.48)
	MKT	1.08***	1.05***	0.03
		(44.07)	(38.80)	(1.06)
	SMB	0.52***	0.65***	-0.12***
		(13.38)	(14.98)	(-2.66)
	HML	0.03	0.19***	-0.16***
		(0.73)	(4.54)	(-3.61)
	XRDF	0.12***	0.05*	0.07**
		(4.73)	(1.89)	(2.23)

(Table OA1 continued)

Models	Variables	Awarded	Unawarded	Awarded-Minus-Unawarded
FF4+XRDF	*Alpha*	0.18*	-0.03	0.21*
		(1.66)	(-0.27)	(1.66)
	MKT	1.07***	1.02***	0.05*
		(43.17)	(38.41)	(1.71)
	SMB	0.53***	0.66***	-0.13***
		(13.50)	(15.73)	(-2.85)
	HML	0.01	0.14***	-0.13***
		(0.31)	(3.43)	(-2.86)
	UMD	-0.05**	-0.16***	0.11***
		(-2.11)	(-6.11)	(3.77)
	XRDF	0.11***	0.03	0.08***
		(4.43)	(1.15)	(2.72)
FF5+XRDF	*Alpha*	0.10	-0.21*	0.31**
		(0.92)	(-1.77)	(2.43)
	MKT	1.09***	1.06***	0.04
		(42.46)	(36.98)	(1.24)
	SMB	0.52***	0.65***	-0.13***
		(13.03)	(14.81)	(-2.85)
	HML	-0.05	0.15***	-0.20***
		(-0.91)	(2.79)	(-3.36)
	RMW	-0.02	0.04	-0.07
		(-0.47)	(0.78)	(-1.13)
	CMA	0.18**	0.07	0.10
		(2.37)	(0.88)	(1.17)
	XRDF	0.11***	0.06*	0.05*
		(4.27)	(1.95)	(1.78)
FF6+XRDF	*Alpha*	0.14	-0.08	0.23*
		(1.35)	(-0.73)	(1.80)
	MKT	1.09***	1.04***	0.05
		(42.18)	(37.46)	(1.63)
	SMB	0.52***	0.67***	-0.14***
		(13.22)	(15.70)	(-3.09)
	HML	-0.08	0.06	-0.14**
		(-1.58)	(1.05)	(-2.29)
	UMD	-0.06**	-0.17***	0.11***
		(-2.58)	(-6.46)	(3.69)
	RMW	-0.01	0.07	-0.08
		(-0.28)	(1.28)	(-1.41)
	CMA	0.21***	0.17**	0.04
		(2.83)	(2.11)	(0.47)
	XRDF	0.10***	0.03	0.07**
		(3.94)	(1.19)	(2.25)

Table OA2: Fama-MacBeth Regression of Award Outcomes

We benchmark the award-return relation with the comparable unawarded stocks. The awarded and unawarded stocks are identified following the methodology that we used in Table 1. We run two-stage Fama-MacBeth cross-sectional regressions to estimate the risk premium of award outcomes. Awarded is a dummy variable indicating whether the firm receives the award in year *t* or not. In Model (1), we report the time-series means of award outcomes with a Newey-West adjustment. In Model (3), we follow (Brennan et al. (1998)) and control for these non-risk security characteristics, which we calculate for each month: PRICE is the natural logarithm of the reciprocal of stock price at the end of month *m*-2; SIZE is the natural logarithm of market capitalization (in billions) at the end of month *m*-2; BM is the natural logarithm of the book-to-market ratio at the end of fiscal year *t*-1, and is winsorized at the 5% and the 95% levels and held constant from July of year *t* to June of year *t*+1; RET2-3, RET4-6, and RET7-12 are the natural logarithm of the cumulative return from months *m*-3 to month *m*-2, from months *m*-6 to month *m*-4, and from months *m*-12 to month *m*-7, respectively, and all in percentage; YLD is the dividend yield calculated as the summation of dividends over the previous 12 months from months *m*-12 to month *m*-1, divided by the stock price at the end of month *m*-2; and DVOL is the dollar volume (in millions) measured by the natural logarithm of trading volume multiplied by stock price at the end of month *m*-2. Besides, we also augment these two models with R&D expenses (in trillions), SG&A expenses (in trillions), and advertising expenses (in trillions) in Models (2) and (4). Numbers without parentheses report parameter estimates, and numbers with parentheses show *t*-values. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively. The span of the time series is from July 1970 to June 2016.

(Table OA2 continued)

Excess return	(1)	(2)	(3)	(4)
Awarded	0.28***	0.37***	0.43***	0.46***
	(7.04)	(7.45)	(7.17)	(9.43)
PRICE			0.25***	0.26***
			(5.22)	(7.62)
SIZE			0.00	0.01
			(0.05)	(0.12)
BM			0.03	0.01
			（0.91)	(0.22)
RET2-3			0.01**	0.01**
			(2.42)	(2.26)
RET4-6			0.01***	0.01***
			(3.68)	(3.37)
RET7-12			0.02***	0.02***
			(2.95)	(3.26)
YLD			6.49**	6.57**
			(2.39)	(2.15)
DVOL			-0.09*	-0.10**
			(-2.03)	(-2.12)
R&D Expenses		-0.22		0.37
		(-0.81)		(1.56)
SG&A Expenses		-0.03		0.06
		(-0.41)		(1.26)
Advertising Expenses		1.33**		1.04*
		(2.18)		(1.87)
Constant	0.65***	0.64***	2.04***	1.99***
	(9.86)	(8.79)	(5.89)	(2.79)
Observations	43,978	43,978	43,978	43,978
# of Months	552	552	552	552

Table OA3: Two-Way Portfolio Sorting on R&D Intensity

This table supplements Table 9 by reporting the excess returns and corresponding alphas and betas of the awarded-minus-unawarded (*AMU*) portfolios in the low R&D intensity group, high R&D intensity group, and high-minus-low group under all factor models. Numbers without parentheses report parameter estimates of excess returns, alphas, and betas, and numbers with parentheses show *t*-values. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively. All estimates are in percentage.

Award \ R&D Intensity		Low	High	High-Minus-Low
Unawarded		0.49	0.51	0.03
		(1.63)	(1.19)	(0.07)
Awarded		0.58*	1.53***	0.95*
		(1.95)	(2.84)	(1.87)
Awarded-Minus-Unawarded (AMU)				
Excess return	***Excess return***	0.09	1.01**	0.92*
		(0.45)	(2.34)	(1.91)
CAPM	***Alpha***	0.09	0.90**	0.81*
		(0.43)	(2.07)	(1.67)
	MKT	0.01	0.22**	0.21**
		(0.17)	(2.31)	(1.99)
FF3	***Alpha***	0.02	1.06**	1.04**
		(0.11)	(2.45)	(2.16)
	MKT	0.06	0.08	0.02
		(1.29)	(0.80)	(0.15)
	SMB	-0.15**	0.37**	0.52***
		(-2.05)	(2.57)	(3.23)
	HML	0.18**	-0.45***	-0.64***
		(2.46)	(-2.96)	(-3.77)
FF4	***Alpha***	-0.10	0.75*	0.85*
		(-0.46)	(1.70)	(1.73)
	MKT	0.09*	0.15	0.06
		(1.82)	(1.47)	(0.52)
	SMB	-0.15**	0.37**	0.52***
		(-2.08)	(2.57)	(3.23)
	HML	0.23***	-0.33**	-0.56***
		(3.04)	(-2.11)	(-3.24)
	UMD	0.13***	0.34***	0.20*
		(2.71)	(3.39)	(1.84)

(Table OA3 continued)

		Awarded-Minus-Unawarded (AMU)		
FF5	***Alpha***	-0.01	1.30***	1.30***
		(-0.03)	(2.93)	(2.67)
	MKT	0.07	0.03	-0.04
		(1.30)	(0.29)	(-0.32)
	SMB	-0.11	0.18	0.29*
		(-1.48)	(1.16)	(1.72)
	HML	0.20**	-0.45**	-0.65***
		(1.98)	(-2.25)	(-2.92)
	RMW	0.12	-0.73***	-0.85***
		(1.20)	(-3.64)	(-3.83)
	CMA	-0.05	0.10	0.15
		(-0.32)	(0.32)	(0.43)
FF6	***Alpha***	-0.11	1.02**	1.13**
		(-0.48)	(2.30)	(2.28)
	MKT	0.09	0.08	-0.00
		(1.64)	(0.78)	(-0.03)
	SMB	-0.12	0.16	0.28*
		(-1.58)	(1.05)	(1.65)
	HML	0.28***	-0.23	-0.51**
		(2.68)	(-1.09)	(-2.18)
	UMD	0.13***	0.38***	0.24**
		(2.69)	(3.79)	(2.19)
	RMW	0.09	-0.81***	-0.90***
		(0.89)	(-4.08)	(-4.07)
	CMA	-0.12	-0.09	0.02
		(-0.76)	(-0.30)	(0.07)
FF3+XRDF	***Alpha***	0.03	1.01**	0.98**
		(0.12)	(2.34)	(2.06)
	MKT	0.07	0.00	-0.06
		(1.32)	(0.03)	(-0.57)
	SMB	-0.13*	0.09	0.23
		(-1.66)	(0.58)	(1.27)
	HML	0.19**	-0.60***	-0.79***
		(2.45)	(-3.83)	(-4.55)
	XRDF	-0.01	0.37***	0.39***
		(-0.29)	(3.58)	(3.37)

(Table OA3 continued)

Awarded-Minus-Unawarded (AMU)				
FF4+XRDF	***Alpha***	-0.10	0.64*	0.74*
		(-0.47)	(1.65)	(1.71)
	MKT	0.09*	0.07	-0.02
		(1.77)	(0.70)	(-0.16)
	SMB	-0.15*	0.05	0.20
		(-1.85)	(0.31)	(1.11)
	HML	0.23***	-0.47***	-0.71***
		(2.95)	(-3.02)	(-4.02)
	UMD	0.13***	0.39***	0.26**
		(2.69)	(3.95)	(2.33)
	XRDF	0.00	0.42***	0.42***
		(0.06)	(4.12)	(3.65)
FF5+XRDF	***Alpha***	-0.01	1.22***	1.22**
		(-0.04)	(2.76)	(2.51)
	MKT	0.07	-0.02	-0.09
		(1.27)	(-0.22)	(-0.77)
	SMB	-0.11	-0.00	0.11
		(-1.38)	(-0.02)	(0.60)
	HML	0.20*	-0.56***	-0.75***
		(1.94)	(-2.71)	(-3.33)
	RMW	0.12	-0.59***	-0.71***
		(1.17)	(-2.88)	(-3.13)
	CMA	-0.05	0.05	0.10
		(-0.32)	(0.16)	(0.29)
	XRDF	0.00	0.29***	0.29**
		(0.05)	(2.74)	(2.46)
FF6+XRDF	***Alpha***	-0.11	0.89**	1.01**
		(-0.51)	(2.03)	(2.04)
	MKT	0.08	0.02	-0.06
		(1.55)	(0.22)	(-0.51)
	SMB	-0.13	-0.06	0.07
		(-1.60)	(-0.35)	(0.40)
	HML	0.27***	-0.32	-0.60**
		(2.60)	(-1.55)	(-2.55)
	UMD	0.14***	0.42***	0.28**
		(2.72)	(4.20)	(2.53)
	RMW	0.10	-0.66***	-0.76***
		(0.96)	(-3.25)	(-3.34)
	CMA	-0.12	-0.17	-0.05
		(-0.79)	(-0.56)	(-0.15)
	XRDF	0.02	0.35***	0.33***
		(0.38)	(3.28)	(2.76)

Table OA4: R&D Investments and the Probability of Winning Awards

We examine the relation between R&D investments and the future probability of being awarded. To do so, we include the whole universe of public firms and run logistic and probit regressions of a dummy variable indicating whether the focal firm receives the award in year t+1 as a dependent variable, and the arithmetic average of R&D expenditures (in trillions) during the previous five years from t-4 to t as an independent variable. We also control for other variables at year t: natural logarithm of market capitalization (*ln(Size)*), natural logarithm of book-to-market ratio *(ln(B/M))*, momentum (*MOM*), SG&A expenses (in trillions), advertising expenses (in trillions), year fixed effects, and industry fixed effects according to the Fama-French 12-industry classification. The sample period is 1969-2014. Numbers without parentheses report parameter estimates, and numbers with parentheses show robust t-values. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Awarded	Logistic								Probit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Avg R&D Expenses	0.23***	0.50***	0.28***	0.54***	0.80***	0.81***	0.57***	0.58***	0.15***	0.41***
	(4.93)	(9.26)	(4.74)	(8.31)	(4.22)	(4.66)	(3.18)	(3.52)	(5.88)	(4.31)
ln(Size)					0.45***	0.76***	0.49***	0.75***		0.22***
					(9.46)	(13.64)	(10.63)	(13.87)		(9.83)
ln(B/M)					0.23**	0.05	0.31***	0.15		0.12***
					(2.49)	(0.50)	(3.30)	(1.45)		(2.70)
MOM					-0.11	-0.31**	-0.12	-0.29*		-0.05
					(-0.95)	(-2.07)	(-1.06)	(-1.93)		(-0.90)
Avg SG&A Expenses					-0.23***	-0.14**	-0.16***	-0.09		-0.11***
					(-3.53)	(-2.27)	(-2.58)	(-1.55)		(-3.26)
Avg Advertising Expenses					-0.04	0.19	-0.02	0.24		-0.0010
					(-0.15)	(0.70)	(-0.07)	(1.01)		(-0.01)
Observations	270,244	270,244	270,244	270,244	76,003	76,003	76,003	76,003	270,244	76,003
R-squared	0.05	0.08	0.14	0.16	0.16	0.25	0.26	0.33	0.07	0.16
Log Likelihood	-5158.54	-5058.32	-4279.75	-4202.18	-1816.01	-1688.97	-1676.95	-1568.31	-5168.3963	-1815.73
Year FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	NO
Industry FE	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO