Product Market Competition, Gross Profitability, and Cross Section of Expected Stock Returns

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ABSTRACT

This paper investigates the interaction between product market competition and profitability on subsequent stock returns. We find that gross profitability premium, which is known as a compensation for risk embedded in firm's expected cash flows, is higher among stocks operating in competitive industries than concentrated industries. Also, competition-return relation is higher among stocks with higher expected profits. Using a conventional double-sorting analysis and regression approach, we find supportive empirical evidence, and the results are robust to other potential factors determining expected stock returns. Furthermore, this difference in the gross profitability premium varying across product market competition is attributed to innovation risk. Empirically, the gross profitability premium among competitive industries is strongly related to the innovation premium. The overall empirical results emphasize the role of product market competition on dissecting the profitability premium and the cross section of expected stock returns.

Keywords: Product market competition, Gross profitability, Financial anomalies, Asset pricing, Stock returns

JEL classification: D43; L22; G12

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1. Introduction

The profitability premium, defined as the return spread between firms of high and low profitability, is intuitively explained by using the dividend discount model in conjunction with clean surplus accounting (Fama and French, 2006). With all else held equal in the dividend discount model, higher expected profitability implies higher expected returns.[1] Recently, inspired by q-theory (Cochrane, 1991), Hou, Xue, and Zhang (2015) have sketched a simple two-period general equilibrium model and prove that the first-order condition of a firm's profit maximization problem implies a positive relation between expected profitability and expected returns. To test the profitability premium empirically, many studies use a variety of current profitability measures as a proxy for future expected profitability. Among them, Novy-Marx (2013) proposes gross profitability, as calculated by the ratio of a firm's gross profits (revenue minus cost of goods sold) to its assets (GPA), as an economically superior proxy for future expected profitability. The author argues that gross profits are the cleanest accounting measure of true economic profitability, in that it considers expensed investments, such as research and development (R&D), advertising, and spending on distribution systems and human capital, which directly reduce current profits but are nonetheless related to future economic profits. In addition, gross profitability as a proxy for expected profitability is widely acknowledged by the literature as having a strong relation with expected stock returns and Novy-Marx (2013) further documents that gross profitability has much stronger predictive power than current earnings in the cross section of stock returns and explains earnings related anomalies and a wide range of seemingly unrelated profitable strategies.[2]

However, the source of risk of gross profitability still remains a puzzle in the asset pricing literature. The valuation model (Fama and French, 2006; Novy-Marx, 2013) and rational explanation of simple q-theory (Hou, Xue, and Zhang, 2015) do not give any answers regarding the determinant of risks, that is, the stochastic discount factor. The empirical analysis by Wang and Yu (2013) advocates that the gross profitability premium could be caused by common mispricing components rather than compensation for risk. In this situation, this paper attempts to propose a source of risk associated with gross profitability, that is, product market competition. Generally, firms' expected cash flows are affected by their operation decisions, which are determined by strategic interactions among product market participants. If firms' expected cash flows are rationally priced in the financial markets, the market price of expected cash flows would reflect the structure of product markets. Therefore, the cross-sectional

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[1] Similar to a mechanical explanation for the value–return relation, Novy-Marx (2013) claims that productive companies' stocks for which investors require high average returns to hold should be priced similarly to less productive companies' stocks for which investors demand lower average returns.

[2] Alternative factor model including gross profitability factor captures the value effect (book-to-markets), momentum, earnings related anomalies (industry-adjusted profitability, return on assets, return on equity, asset turnover, and gross margins), investment anomalies (asset growth and net stock issuance), and lottery related anomalies (failure probability and O-score).

pricing impacts of gross profitability, which is a better accounting proxy for future expected profitability, should be affected by product market competition.

This paper empirically finds the positive joint effect of product market competition and gross profitability on the cross section of expected stock returns. Basically, opportunities to make profits dry up more quickly in a highly competitive market due to the entrance of competitors and current profits can be easily taken away by competitors in a highly competitive market. Thus, firm productivity is more threatened by rivals in more competitive product markets, hence, firms in different product markets are fundamentally different, even though they have the same expected future cash flow. Investors demand higher compensation for holding productive stocks in highly competitive industries compared to stocks of similar productivity in concentrated industries. Our novel empirical findings suggest that the gross profitability premium is stronger in competitive industries.

This paper uses three product market competition proxies to examine the joint effect of competition and gross profitability on stock returns. The first proxy is the fitted Herfindahl–Hirschman Index (*Fit_HHI*) using a sample that includes both public and private companies, proposed by Hoberg and Phillips (2010). This version of the Herfindahl–Hirschman Index could well capture product market structure, in that it considers the additional impact of private firms. The second proxy is a measure of firm-specific competitive pressure (*Fluidity*), developed by Hoberg, Phillips, and Prabhala (2014). This measure captures the similarity between a firm's products and changes in the products of competitors, so greater similarity implies greater threats by competitors. These two variables are available from the Hoberg–Phillips Data Library.[3] The last measure is the original Herfindahl–Hirschman Index using the Compustat Segment database merged with the Compustat database (*Comp_HHI*) to add robustness to the empirical results. The three measures cover different testing periods: *Fit_HHI* covers from 1975 to 2005, *Fluidity* covers from 1997 to 2015, and *Comp_HHI* covers from 1976 to 2016. Due to the different coverage periods of the competition measures, we first check the gross profitability premium in different periods and find strong risk-adjusted performance. Quintile portfolios analysis shows that risk-adjusted spreads range from 0.41% (0.63%) to 0.49% (0.71%), based on value-weighted (equal-weighted) portfolios and are statistically significant.

Using a conventional double-sorting analysis, we show a robust positive interactive effect between product market competition and gross profitability. At the end of June of each year t, we divide stocks into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of ranked values of the competition proxy in year $t - 1$ and independently divide the stocks into five groups based on the ratio of GPA in year $t - 1$. Throughout the double-sorted portfolios analysis, we first find that the gross profitability premium is much greater in competitive industries than in concentrated industries. Specifically, based on the analysis using *Fit_HHI*, the risk-adjusted gross profitability premium in

[3] See http://hobergphillips.usc.edu.

competitive (concentrated) industries is 1.24% (0.17%), with a t-statistic of 3.60 (0.58). These empirical results are quantitatively similar to those using *Fluidity* and *Comp_HHI* and these significant differences in growth profitability premium are also confirmed with a different weighting scheme, dependent double-sorting analysis, and portfolio sorting based on New York Stock Exchange (NYSE) breakpoints.

The impact of product market competition on the gross profitability premium is robust to Fama–MacBeth (1973) cross-sectional regressions. We use the interaction terms of gross profitability with a high-competition dummy variable to indicate stocks categorized in the top 30% of high competition groups based on competition measures in the fiscal year $t - 1$ and find that the cross-sectional impact of gross profitability on future stock returns is significantly higher for firms in competitive industries. These effects are robust to other firm characteristics affecting the cross section of stock returns.

Furthermore, this paper finds that a positive competition–return relation, documented by Hou and Robinson (2006), only appears among productive groups. For example, based on the double-sorting analysis using *Comp_HHI* as a proxy for competition, the average risk-adjusted value-weighted portfolio returns of the highest gross profitability group in competitive (concentrated) industries is 0.59% (0.13%), with a t-statistic of 4.44 (1.01), and their difference is statistically significant. On the other hand, this competition–return pattern does not appear in the lowest gross profitability group. The average portfolio returns among the lower gross profitability groups are nevertheless weaker in competitive industries than in concentrated industries. We interpret these different empirical patterns to the different mechanisms of the risk channels of competition. Generally, firms seek higher expected returns on projects and are therefore more likely to enter highly profitable markets, so competition could act as a threat to incumbent participants (Hou and Robinson, 2006) only in a profitable product market. In contrasts, competition could act as a barrier to entry in a less profitable product market (Bustamante and Donangelo, 2017). These opposite effects of competition result in those empirical results. Even though the positive competition–return relation in the productive groups is not always statistically significant, the overall empirical results support a positive interaction effect between product market competition and gross profitability.

If investors demand higher compensation for a risk on expected profitability in highly competitive industries than that in concentrated industries, one of the economic reasons is that investors add value on smooth cash flows. (e.g., Froot, Scharfstein, and Stein, 1993) Gaspar and Massa (2006) and Irvine and Pontiff (2008) document that firms in highly competitive product markets have greater idiosyncratic volatility due to the higher uncertainty of future cash flows. In this regard, we test whether product market competition does affect the uncertainty of gross profitability. We estimate Fama–MacBeth (1973) cross-sectional regression to examine the effects of product market competition on the future volatility of profitability, and confirm that market competitiveness significantly impacts the uncertainty of future profits. Specifically, in industry level, product market competition increases the future dispersion of profits within an industry. In addition, by conducting a firm level analysis, we find that the firm-specific future earnings volatility is positively related to competition. This result is also robust to controlling for other characteristics that could be related to a firms' earnings volatility.

So far, we confirm that expected returns on expected profitability are greater in competitive industries. Then, it is natural to ask the source of driving force of a pricing kernel since equilibrium asset price is expressed as the expected product of a pricing kernel and the cash flows from the asset. In this study, we proposes the risky innovation as a potential determinant of a pricing kernel on expected profitability. According to Schumpeter (1912), corporate profits arise from entrepreneurial innovation and such innovations are more likely to occur in competitive industries. Thus, firms in competitive industries are more likely to be engaged in innovation to maintain their profitability and competitiveness and innovation is generally a risky operating process. In the real options model developed by Berk, Green, and Naik (2004), R&D investments are a series of compound options on the systematic component of risk associated with cash flows and these R&D ventures demand a higher risk premium than stochastic cash flows, because the risk of options is higher than that of underlying assets. Therefore, the mechanism of this paper's empirical findings is probably related to the innovation premium.

To inspect the linkage between the gross profitability premium varying across levels of product market competition and innovation, we further conduct a portfolio analysis. We utilize R&D intensity measure as a proxy for firms' innovative operations. Throughout the same double-sorting analysis, we find that the difference between R&D intensity is much greater in competitive industries within the same quintile of GPA portfolios. Specifically, in the case of *Fit_HHI* as a proxy for competition, among the firms in competitive industries, the average R&D intensity of the highest (lowest) quintile of GPA portfolios is 0.040 (0.001) and the difference between them is statistically significant, with a t-statistic of 5.69. However, in concentrated industries, the average R&D intensity of the highest (lowest) GPA quintile portfolios is 0.019 (0.021) and the difference is even negative and statistically insignificant. These results suggest that firms in competitive product markets are more likely to be engaged in innovation, even though they have the same expected profitability. Secondly, using the R&D premium based on the R&D intensity measure, we find that gross profitability spreads are only positively exposed to the R&D premium in competitive industries. The overall empirical results suggest that the market price of the risk of gross profitability is related to risky innovation (Berk, Green, and Naik, 2004; Hou and Robinson, 2006).

Lastly, we check the empirical robustness on the mispricing explanations for profitability premium. Wang and Yu (2013) document a gross profitability premium primarily among firms with high arbitrage costs, high arbitrage risk, and high information uncertainty. To control for the interaction effects of information uncertainty and limits to arbitrage, we conduct a Fama–MacBeth (1973) regression using interaction terms with proxies for arbitrage risk and information uncertainty. In summary, the effect of competition is robust to mispricing channels.

This paper makes two main contributions. First, it contributes to the literature on dissecting the gross profitability premium. One strand of literature documents that the gross profitability premium is compensation for risk (e.g., Fama and French, 2006; Kogan and Papanikolaou, 2013, 2014; Novy-Marx, 2013; Hou, Xue, and Zhang, 2015). The other strand proposes empirical evidence supporting the idea that misevaluation or mispricing could lead to the higher average returns of productive firms. (e.g., Stambaugh, Yu, and Yuan, 2012; Wang and Yu, 2013; Ball, Gerakos, Linnainmaa, and Nikolawv, 2015; Lam, Wang, and Wei, 2015). Due to the lack of empirical evidence indicating that the gross profitability premium is a compensation for risk, this paper attempts to provide empirical evidence supporting the first strand of literature.

Also, there is a few remarkable studies attempting to dissect the gross profitability premium using a general equilibrium model. The recent theoretical model developed by Kogan and Papanikolaou (2013) implies that firms with more growth opportunities than assets in place have greater exposure to technological shocks, which are negatively priced; so firms with high profits derive most of their value from existing assets rather than growth opportunities and have lower exposure to technological shocks and higher average returns. However, this model does not capture the different product market environments and focuses on current rather than expected profitability. Since firms' expected profitability is more strongly related to their growth options or innovative investments, in which uncertainty is embedded (Berk, Green, and Naik, 2004), the risk associated with this uncertainty varies across interactions with product market competition (Hou and Robinson, 2006). In this regard, this study provides an empirical hint at another pricing mechanism of expected profitability, which involves product market competition and rival risk, and could contribute to establishing the empirical basis for the use of profitability-based asset pricing models (e.g., Novy-Marx, 2013; Fama and French 2015, 2016; Hou, Xue, and Zhang, 2015).

Second, this study contributes to the literature on the relation between competition and the cross-section of stock returns. Hou and Robinson (2006) document that firms in more concentrated industries earn lower returns, even after controlling for common risk factors. Based on a real option model, Aguerrevere (2009) shows that firms in more competitive industries earn higher returns during times of weak demand, while firms in more concentrated industries earn higher returns during times of strong demand. Using an equilibrium model, Lyandres and Watanabe (2012) finds that the expected returns of firms with reliable (unreliable) products decrease (increase) with product market competition. Gu (2016) documents that R&D-intensive firms are riskier and earn higher average returns than less R&D-intensive firms, but only in highly competitive industries. In this paper, we find that another crucial role of product market competition in determining the risk premium between firms with high and low expected profitability. The recent model of Bustamante and Donangelo (2017) documents that riskier industries become less competitive because the threat of new entries lowers the systematic risk of existing market participants due to a high entry barrier in competitive industries, in contrast to the results of Hou and Robinson (2006). However, the threat of entry by new firms is not the only source of risk in product markets and, in this paper, we argue that firms with higher expected profitability in more competitive markets have greater exposure to innovation risk and, hence, have higher average returns.

The remainder of this paper is structured as follows. Section 2 describes the data and the main variables. Section 3 proposes the empirical results for the interactive effects of gross profitability and product market competition. Section 4 empirically examines the impact of product market competition on the uncertainty of profitability. Section 5 dissects the risk sources of competition on expected profitability by focusing on innovation premium. Section 6 adds robustness of our empirical results on the mispricing explanation of profitability premium. Section 7 summarizes the results and makes concluding remarks.

2. Data and competition measures

In this section, we provide descriptions of the data, the sample used in the empirical analysis, and the methodology of constructing the main product market competition variables (*Fit_HHI*, *Fluidity*, and *Comp_HHI*).

2.1 Data and sample

Our sample includes all publicly traded firms in Compustat in fiscal years 1975 to 2016, due to the availability of competition data. The accounting data are merged with monthly stock return data extracted from the Center for Research in Security Prices (CRSP), including only common stocks traded on the NYSE, AMEX, and NASDAQ (firms with share codes 10 and 11 and exchange codes 1 to 3). Our sample excludes financial firms (with four-digit Standard Industrial Classification, or SIC, codes between 6000 and 6999), regulated utility firms (with four-digit SIC codes between 4900 and 4999), and firms with negative book equity. We also exclude firms with a closing price of less than $1 to alleviate the effects of micro stocks.

Following Fama and French (1993), we match accounting data for all fiscal year-ends in calendar year $t - 1$ with CRSP stock return data from July of year t to June of year $t + 1$ to ensure a minimum time gap. This half-year gap at the minimum between fiscal year-ends and stock returns provides enough time for accounting information to be incorporated into stock prices. Since firms have different fiscal year-ends, this time gap between accounting data and monthly stock data varies across firms.

Similarly, all three kinds of competition measures in year t are used at the end of June of year $t + 1$, when portfolios are formed. This is because competition measures are constructed based on publicly offered accounting reports. The three competition measures cover different testing periods because of data availability: *Fit_HHI* covers from 1975 to 2005, *Fluidity* covers from 1997 to 2015, and

Comp_HHI covers from 1976 to 2016.[4] Due to the coverage of the different competition measures, we have three testing periods: July 1976 to June 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). The details of the construction methodology of these competition proxies are introduced in the next subsection.

2.2 Measurement of product market competition

The most common measurement of product market competition is the Herfindahl–Hirschman Index (HHI; e.g., Hou and Robinson, 2006; Hoberg and Phillips, 2010; Gu, 2016) The HHI is defined as the sum of squared market shares within each industry:

$$HHI_{jt} = \sum_{i=1}^{N_j} s_{ijt}^2$$

where s_{ijt} is the market share of firm *i* in industry *j* in year *t* and N_j is the number of firms operating in industry *j* in year *t*. The market share of an individual firm is computed by using firms' net sales divided by the total summation of sales of the entire industry. In this paper, following the standard methodology in the previous study (e.g., Hou and Robinson, 2006; Gu, 2016), the industry classification is based on three-digit SIC codes from the CRSP, because those from the CRSP report the time series of industry classification codes while Compustat reports only the most recent SIC codes.[5] All firms with non-missing sales values are included in the sample to calculate the HHI for each industry.

Measurements of the HHI are divided into two parts; market share and industry classification. For the first part, market share, the literature commonly uses Compustat annual net sales (item SALE) to calculate market shares (e.g., Gu, 2016). However, in this paper, we use segment information to compute the HHI for each industry (e.g., Li, 2010), because it was in 1976 that SFAS No. 14 started requiring multi-industry firms to disclose sales, earnings, and cash flows from operations in each industry segment that comprises more than 10% of a firm's total consolidated annual sales. As documented by Cohen and Lou (2012), after appropriate screening procedures, almost one-third of firm–year

[4] The Hoberg and Phillips Data Library provides data for the fitted HHI from 1975 to 2005. In addition, the fluidity data start in 1997, because of the required availability of machine-readable 10-K forms. Our final sample covers 1976 to 2016, which includes the most recent fiscal year-end and starts in 1976 due to that being the first year firms were mandated under Statement of Financial Accounting Standards (SFAS) No. 14 (Financial reporting for segments of a business enterprise).

[5] As noted by Gu (2016), an extremely fine-grained industry classification results in statistically unreliable portfolios and, if the classification is not sufficiently fine grained, firms in different businesses could be grouped together. Therefore, we choose a three-digit SIC code to classify industries (e.g., Hou and Robinson, 2006; Hoberg and Phillips, 2010).

observations in the Compustat Segment database are associated with conglomerate firms.[6] Therefore, using segment-level data to measure the market share is more accurate than using firm-level total sales.[7]

Before merging the Compustat segment database with Compustat's annual file, we delete firms incorporated outside the United States because firms operating outside the United States are likely to face a different product market. Then, we extract data on non-missing net sales (item SALES) for only business segments (item type BUSSEG) with a valid primary four-digit SIC code (item SIC1) and all the net sales data are aggregated if they have the identical SIC code under the same firms. Extracted data are merged with the Compustat annual file and firms without segment information are considered to have a single segment and we treat total net sales in Compustat as segment sales. Finally, we merge this sample with the CRSP database at the end of June of each year and classify firms into different industries according to their primary SIC code that matches with the CRSP SIC code. If a firm has multiple business segments, the segment with the same four-digit SIC code as the CRSP SIC code is identified as the primary segment. If none of the segments has the same SIC code as the firm, then the segment with the largest sales is treated as the primary segment.[8] Finally, using this merged data set, we measure the HHI for each industry and assign an annual HHI to each firm operating in the industry based on the CRSP's three-digit SIC codes. We label this variable *Comp_HHI* throughout this study.

Regarding the second part of the HHI, industry classification, Ali, Klasa, and Yeung (2009) argue that Compustat-based industry competition measures are subject to measurement error, because most private firms are not covered by Compustat, and therefore highlight the importance of considering both private and public firms in constructing measures of concentration. Alternatively, Ali et al. (2009) suggest that researchers should use a competition measure from a concentration ratio provided by US Census data. However, the US Census measure of the concentration ratio is only available for short periods of the sample and only for the manufacturing industries. Thus, using US Census data to capture an effect of private firms would reduce the sample size significantly, thereby contradicting the aim of this paper to provide large-sample evidence. To mitigate concerns regarding an effect of private firms, we use the fitted HHI developed by Hoberg and Phillips (2010), because it captures the impacts of both public and private companies on industry competitiveness.

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[6] Cohen and Lou (2012) merge samples from the Compustat Segment database with the Compustat annual database from 1976 to 2009 and, based on two-digit SIC codes, define conglomerate firms as firms operating in more than one industry and whose aggregate sales from all reported segments account for more than 80% of the total sales reported in the Compustat annual file. The authors exclude firms that failed to report financial data for some industry segments (less than 80% of total sales are reported in the Compustat segment database) and exclude stocks priced below $5. Because we use three-digit SIC codes to classify industries, our sample would contain a higher percentage of conglomerates than that used by Cohen and Lou (2012).

[7] By using the same procedure, we could construct the HHI with firms' total net sales from the Compustat annual file. The alternative measure of *Comp_HHI* produce qualitatively similar results.

[8] This methodology is consistent with the way the SIC assigns the primary SIC code to each firm. (Li, 2010)

Combining Compustat data with Herfindahl data from the US Department of Commerce and employee data from the Bureau of Labor Statistics (BLS), Hoberg and Phillips (2010) use a two-step procedure to calculate the fitted HHI for all industries. First, for the subsample of manufacturing industries where actual HHIs including both public and private firms exist in the Herfindahl data from the Department of Commerce, the authors regress the actual industry HHI on the Compustat-based HHI for only public firms, the average number of employees per firm using the BLS data (including both public and private firms), the number of employees per firm using the Compustat data (including only public firms), and the interaction variables of firm size and the Compustat-based HHI. In the second step, using the coefficient estimates from the first-step regression, the authors compute the fitted HHI values for all industries in each year. The detailed construction methodology of the fitted HHI is introduced by Hoberg and Phillips (2010) and this annual competition proxy is available for the period from 1975 to 2005. We label this variable *fit_HHI* in this paper and we download the data from the Hoberg–Phillips Data Library.

The two HHIs mentioned above are industry-level proxies for product market competition. Hoberg, Phillips, and Prabhala (2014) argue that the HHI is static and based on historical information on firm market shares and it is hard to incorporate the dynamic actions of a firm's rivals. Thus, the authors propose a new competition proxy that could capture the firm-specific information that industry-level measures could not. Using text-based analysis of the 10-K of all firms, they measure product market fluidity by calculating the cosine similarity between a firm's products and the changes of the products of competitors in that firm's product markets. This similarity is a forward-looking measure of the competitive threat of rival firms; hence, higher similarity implies greater threats by competitors. Hoberg et al. (2014) show that this fluidity, even though it measures threats from public firms through 10-Ks, is significantly correlated with competitive threats from private firms. This measure is an annual firm-level proxy for product market competition covering the period from 1997 to 2015 and we label it *Fluidity* in this paper. The detailed construction methodology of *Fluidity* is introduced by Hoberg et al. (2014) and is also available in the Hoberg–Phillips Data Library. As we mention above, since the three kinds of competition proxies cover different periods, our test periods vary depending on which competition variable is used.

2.3 Measurement of expected profitability and innovation intensity

To measure firms' expected profitability, we use the gross profits-to-assets ratio (*GPA*) as total revenue (Compustat annual item REVT) minus the cost of goods sold (item COGS) divided by lagged total assets (item AT). Novy-Marx (2013) argues that gross profits are the economically cleanest accounting measure of true expected profitability, in that it considers expensed investments, such as R&D, advertising, and spending on distribution systems and human capital, which directly reduce current profits but are nonetheless related to future economic profits. These authors further document that gross profitability has much stronger predictive power on the cross section of stock returns than other current earnings and factor-mimicking portfolios based on gross profitability explain most earnings-related anomalies, as well as a wide range of seemingly unrelated profitability trading strategies. Additional tests further show that the effect is not driven by illiquidity and that it also holds for international data.

Second, a firm's innovative intensity is measure by R&D expenditures scaled by market equity (RD/ME). Hou, Xue, and Zhang (2015) find that RD/ME significantly predicts stock returns, but other measures of R&D intensity, for instance, RD/Sales and RD capital/Assets, fail to have a significant cross-sectional price impact. In addition, Gu (2016) dissects the R&D premium based on RD/ME incorporating product market competition. Thus, we use RD/ME to measure firms' innovative intensity in this paper.

2.4 Descriptive statistics

This study covers an extensive sample of all US firms exchanged on the NYSE, AMEX, and NASDAQ with the proper filtering procedures described above. The sample period is from July 1976 to December 2016 and the empirical analysis with each competition proxy covers different periods. Table 1 describes the descriptive statistics and the correlation matrix of the main variables in this study.

[Table 1 about here]

Panel A of Table 1 presents descriptive statistics of three competition measures, *Fit_HHI*, *Fluidity*, and *Comp_HHI*, as well as gross profitability in the monthly basis sample. There are significant differences in the numbers of observations because of the different coverage periods July 1976 to June 2007 (*Fit_HHI*), July 1998 to December 2016 (*Fluidity*), July 1977 to December 2016 (*Comp_HHI*), and July 1976 to December 2016 (*GPA*). In addition, some firms do not have a valid SIC code to match the corresponding competition measures. All four main measures have similar averages and medians.

Panel B of Table 2 reports the correlation matrix of the four measures. The upper (lower) triangle matrix presents the Pearson (Spearman) correlation matrix. All three kinds of competition proxies have a strong cross-sectional relation. Hoberg and Phillips (2010) note that the fitted HHI and the Compustat-based HHI are correlated, but the fitted HHI is more correlated with the actual HHI provided by the Department of Commerce. We use both kinds of HHIs to verify the robustness of the empirical results. The firm-specific measure of competition, *Fluidity*, also has an economically strong correlation with the two industry-level competition measures and the cross-sectional correlation is strong with *Fit_HHI* than with *Comp_HHI*, implying that *Fit_HHI* is more suitable for reflecting product market competitiveness than the Compustat-based measure is. Furthermore, *Fluidity* is highly correlated with

GPA cross-sectionally, suggesting that the profitability of firms with greater product market threats is damaged by rival firms.

3. Product market competition and stock returns

In this section, we examine the interaction effect between product market competition and gross profitability. We conduct a portfolio analysis and Fama–MacBeth (1973) cross-sectional regressions. For the portfolio analysis, we control for common risk factors using Carhart's (1997) four-factor model.

3.1 Univariate portfolio analysis

Due to the differences in coverage of the three kinds of competition measures, we first check the gross profitability premium in the different periods. Using conventional univariate portfolio analysis, we confirm significantly higher expected returns for firms with high expected profitability. At the end of June of each year *t*, we divide stocks into five portfolios based on the *GPA* values of the fiscal year *t* – 1 and the quintile portfolios are rebalanced annually at the end of June.

[Table 2 about here]

Table 2 reports the results of univariate sorts based on *GPA* for each testing period. Panels A to C report the gross profitability premium on the periods covered by *Fit_HHI*, *Fluidity*, and *Comp_HHI*, respectively. For brevity, we only report the risk-adjusted performance of the lowest, middle, and highest portfolios and the difference between the highest and lowest portfolios, both value and equal weighted. Furthermore, since Novy-Marx (2013) conducts a portfolio analysis based on NYSE breakpoints, we repeat the analysis based on NYSE breakpoints and report the results in the Appendix. Overall, the univariate analysis shows a significant gross profitability premium when controlling for common risk factors.

We also report the average characteristics of each quintile portfolio. As documented by Novy-Marx (2013), the book-to-market ratios are negatively related to gross profitability because firms with higher growth options have greater expected profitability. The R&D intensity (RD/ME) and competition proxies do not have definite relevance to gross profitability, except in Panel B. In the case of R&D intensity, since the average RD/ME value of the second and fourth portfolios is dropped, the actual relation to *GPA* is not monotonically decreasing. However, as confirmed in the correlation matrix, product market threats and expected profitability are negatively related, because higher profits are expected in industries with lower market threats.

3.2 Double sorts with gross profitability and product market competition

Using a conventional double-sorting analysis, we begin by investing the interaction effect between product market competition and expected profitability. At the end of June of each year *t*, we divide stocks into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of ranked values of the competition proxy in year *t* – 1 and independently divide stocks into five groups based on the ratio of gross profits to assets in year *t* – 1. The portfolios are rebalanced annually at the end of June.

[Table 3 about here]

Table 3 reports the results of the performance of double-sorted portfolios. We reports two kinds of weighting schemes (value and equal weighted) and both the mean excess return and risk-adjusted alphas. To conserve space, we only report the lowest and highest competition terciles of and the lowest, middle, and highest quintiles of the *GPA* axis. Panels A and C report the average returns on the periods covered by *Fit_HHI*, *Fluidity*, and *Comp_HHI*, respectively. Since *Fit_HHI* and *Comp_HHI* decrease as product market competition intensifies, the low (high) competition columns of Table 3 present the highest (lowest) terciles based on the corresponding competition proxy. In contrast, the low (high) competition columns of Table 3 present the lowest (highest) terciles based on *Fluidity*. The last columns report the differences of the average excess returns and risk-adjusted returns of the high and low competition terciles.

First, the return on the high-minus-low *GPA* portfolio is stronger in competitive industries than in concentrated industries and all the differences are statistically and economically significant. For instance, when the analysis uses *Fit_HHI* as the competition proxy, the monthly value-weighted return to the high-minus-low *GPA* quintile portfolio in competitive industries (high competition) is 1.11%, with significance at 1%. On the contrary, the return in concentrated industries (low competition) is 0.16%, with a t-statistic of 0.57. Similar to the analysis with *Fit_HHI*, the analysis based on the other two competition measures shows that the growth profitability premium is higher in competitive industries. The monthly equal-weighted return to the high-minus-low *GPA* quintile portfolio shows significant differences even in the lowest competition tercile; nonetheless, the difference between the averages of the high-minus-low spreads in competitive and concentrated industries is statistically significant. Specifically, when the analysis uses *Fit_HHI* as the competition proxy, the difference in the monthly equal-weighted returns to the high-minus-low *GPA* portfolios is 0.76%, with a t-statistic of 3.08. The overall empirical results of Table 3 support our main hypothesis that the risk premium of higher expected profits is increased in competitive industries.

Second, we investigate the cross-sectional relation between stock returns and product market competition. Hou and Robinson (2006) argue that competitive industries have higher innovation risk; hence, firms in competitive industries earn higher stock returns. These authors also find the distress risk channel to be the likely culprit for this competition premium, because the barriers to entry in highly concentrated industries insulate firms from undiversifiable distress risk, but their overall findings support the interpretation of innovation risk. On the other hand, Bustamante and Donangelo (2017) argue a higher barrier to entry exists in competitive industries, in contrast with Hou and Robinson (2006), and document a negative relation between competition and stock returns.

Even though the results are not strongly statistically significant, we find different competition–return relations depending on firms' expected profitability. Firms with high expected profits (higher value of gross profitability) show positive competition–return relations; however, firms with low expected profits (lower value of gross profitability) exhibit negative competition–return relations. For example, when the analysis uses *Comp_HHI* in Panel C of Table 3, the monthly value-weighted risk-adjusted returns of the highest *GPA* quintile (labeled GPA5) is 0.59%, with 1% statistical significance in competitive industries, but the monthly value-weighted alpha in concentrated industries of the highest *GPA* quintile is only 0.13%, with a t-statistic of 1.01, exhibiting a positive competition–return relation. In contrast, when the analysis uses *Fit_HHI*, the monthly value-weighted risk-adjusted returns of the lowest *GPA* quintile (labeled GPA1) is -0.79% (-0.05%), with a t-statistic of -2.77 (-0.24) in competitive (concentrated) industries, and the difference is statistically significant. In the lowest *GPA* quintiles, the overall relations between product market competition and stock returns are almost negative.

We attribute the different relations depending on firms' expected profits to the different mechanisms of the risk channels of competition. Generally, firms seek higher expected returns on projects and are therefore more likely to enter highly profitable markets. Therefore, competition in a profitable product market could act as a threat to incumbent participants (Hou and Robinson, 2006), but it could act as a barrier to entry in a less profitable product market (Bustamante and Donangelo, 2017). Furthermore, firms do not take risks in less profitable projects. Because of these opposite effects of competition, firms more likely to be engaged in innovative projects to maintain their profitability only in profitable product markets, so the innovation channel of the competition premium is severely increased in profitable markets. These different mechanisms of the risk channel of product market competition result in these empirical differences.

[Table 4 about here]

Our main results are unchanged when we sort stocks dependently. Table 4 presents the results based on the dependent double-sorting analysis. First, we divide stocks into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of ranked values of the competition proxy in year $t - 1$ and then, depending on the competition terciles, we divide stocks into five groups based on the ratio of gross profits to assets in year $t - 1$. The main empirical results are robust. The gross profitability premium is much larger in competitive industries and the differences in the gross profitability premium between the highest and lowest competition terciles are almost all statistically significant. Specifically, when analyzed with *Fluidity*, the monthly value-weighted risk-adjusted returns to the high-minus-low *GPA* quintile portfolio in competitive industries (high competition) is 0.79%, with a t-statistic of 1.87. On the contrary, the alpha in concentrated industries (low competition) is -0.03%, with a t-statistic of -0.10. The average difference between these two risk-adjusted spreads is 0.82%, with a t-statistic of 1.72. The double-sorting analysis with NYSE breakpoints is also statistically robust. The results based on NYSE breakpoints are reported in the Appendix.

3.3 Fama–MacBeth regression

The conventional double-sorting analysis in the previous subsection documents that the risk premium on the expected profitability is much larger or only present in competitive industries, which is our main finding. However, this finding could be driven by other factors that might be related to the *GPA*–return relation. Since other potential driving forces are not adequately controlled for in the portfolio analysis, in this subsection, we examine the impacts of other possible forces by running Fama–MacBeth (1973) cross-sectional regressions. Our regression specification is

$$Excess\ Return_{i,t+1} = \alpha + \beta_0 GPA_{i,t} + \beta_1 HighCompetition_t$$
$$+\beta_2 GPA_{i,t} HighCompetition_t + Controls_{i,t} + \epsilon_{i,t+1}$$

where $Excess\ Return_{i,t+1}$ is the excess return of stock *i* in month *t* + 1, $GPA_{i,t}$ is the gross profitability of firm *i* in month *t*, $HighCompetition_t$ is a dummy variable indicating that firm *i* is operating in the top 30% of ranked values of product market competitiveness in month *t*; and $Controls_{i,t}$ includes the firm size, the book-to-market ratio, the past 1-month returns, the past 11 months of returns skipping one month, idiosyncratic volatility, illiquidity, and R&D intensity. The variable constructions are described in the Appendix. The independent variables are trimmed at the 1% and 99% levels to reduce the impact of outliers.

[Table 5 about here]

The coefficient of interest is the regression coefficient of the interaction of gross profitability and a dummy variable indicating high product market competition, which is β_2 in the above specification. Table 5 reports the results of the Fama–MacBeth (1973) cross-sectional regression and β_2 is expressed as *GPA*Dummy(High)* in Table 5. There are three kinds of regression specifications: one with no additional control variables; one controlling for size, the book-to-market ratio, short-run reversal, and price momentum; and one controlling all the other factors.

Except for the analysis based on *Fluidity*, all the coefficients of the interaction terms are highly statistically significant. The analysis based on *Fluidity* also shows significant interaction when we do not control for idiosyncratic volatility, illiquidity, and RD/ME. The reason for losing significance could be the relation between *Fluidity* and RD/ME. Nevertheless, the coefficient of the interaction term is almost significantly positive, implying that gross profitability, a proxy for expected profitability, predicts the expected stock returns with greater significance in competitive industries.

Taken together, the results of the two conventional empirical tests on the cross section of stock returns, that is, the portfolio analysis and the regression approach, suggest that the gross profitability premium is greater in competitive industries. In addition, the competition–return relation varies with firms' expected profitability. This empirical evidence emphasizes the role of product market competition in explaining the gross profitability premium and the interaction between market competition and gross profitability in the cross section of expected stock returns.

4. Product market competition and the uncertainty of profitability

In this section, we investigate the impact of product market competition on the uncertainty of profitability. First, we analyze the relation between industry-level competition and the industry-wide dispersion of gross profitability. Then, using Fama–MacBeth (1973) cross-sectional regression, we examine the impacts of product market competition on the future volatility of gross profitability.

4.1 Industry-wide dispersion of gross profitability

If product market competition intensifies the systematic risk on expected profitability, firms in competitive industries have greater uncertainty of expected profitability than those in concentrated industries. To confirm this result, we first conduct industry-level analysis. Irvine and Pontiff (2008) argue that more concentrated industries have a lower cross-sectional dispersion of profitability. Industries with greater dispersion of profitability among firms present higher cross-sectional differences of expected profits among firms, implying that firms' earnings are more likely to be extinguished by rival firms in competitive markets.

Using a correlation matrix and a regression approach, we examine the impact of product market competition on the future dispersion of gross profitability. Since this is an industry-level analysis, we do not include *Fluidity* in this analysis. The dispersion of gross profitability in year t is calculated as the standard deviation of *GPA* within the same industry in year t. Panel A of Table 6 presents the time series average of the cross-sectional correlation between competition proxies and the contemporaneous and future dispersion of gross profitability. Given that higher values of HHI are likely to be associated with more skewed, or scattered, distributions of profitability, we find that there are negative relations between the competition proxies and contemporaneous and future (up to three years) dispersions of gross profitability. The results show that the distribution of profitability is more scattered in a competitive industry.

[Table 6 about here]

Panel B of Table 6 shows the results of the regression approach. The dependent variables are the future dispersion of gross profitability up to three years and the main independent variables are industry-wide *Fit_HHI* and *Comp_HHI*. We control for industry-level profitability and report t-statistics based on two-way clustered standard errors to control for time and industry fixed effects. We only report the regression coefficients of *Fit_HHI* and *Comp_HHI* to conserve space. All the coefficients of the competition measures are negative and statistically significant, showing that product market competition increases the uncertainty of future profitability.

4.2 Future volatility of gross profitability

In this subsection, we examine the role of product market competition in determining firms' individual earnings volatility. Gaspar and Massa (2006) document that firms enjoying market power and operating in concentrated industries have lower idiosyncratic volatility. Similarly, firms in concentrated product markets have lower uncertainty of profitability and lower future volatility of cash flows. We conduct a Fama–MacBeth (1973) regression to investigate the impact of competition on the future volatility of gross profitability. This is a direct test examining the relation between product market competition and the uncertainty of profitability. Our regression equation is as follows:

$$Vol(GP)_{i,t+1\sim t+k} = \alpha + \beta_0 vol(GP)_{i,t} + \beta_1 Competition_{i,t} + \beta_2 \, log\left(ME_{i,t}\right) \\ + \beta_3 \frac{RD_{i,t}}{ME_{i,t}} + \beta_4 IVOL_{i,t} + \beta_5 GPA_{i,t} + \epsilon_{i,t+1} \quad \text{where } k \in \{2,3,4\}$$

where $Vol(GP)_{i,t+1\sim t+k}$ is the future volatility of the gross profitability of firm *i* in years *t* + 1 to *t* + *k*, and $Competition_{i,t}$ is one of the three competition measures. We control for firm size, R&D intensity, firm-specific idiosyncratic risk, and current gross profitability, which could affect the future volatility of profitability. We also control for non-overlapping lagged *GPA* volatility to erase an autoregressive component of the dependent variable and the independent variables are trimmed at the 1% and 99% levels to reduce the impacts of outliers.

[Table 7 about here]

Panels A to C of Table 7 report the regression results based on the two-, three-, and four-year volatility of *GPA*, respectively. Almost all the coefficients of competition are statistically and economically significant. For example, in Panel B, the regression coefficients of *Fit_HHI* and *Comp_HHI* are negative and highly statistically significant and the significance of the coefficient of *Fluidity* is much greater. The autoregressive property of earnings volatility is also statistically significant. Size is negatively related to the future profitability of gross profitability. This is because smaller firms are more volatile and have greater distress risk (Fama and French, 1992); hence, smaller firms' expected profits are more volatile. Similarly, idiosyncratic firm-specific risk increases the volatility of gross profitability. Furthermore, research intensity significantly increases the uncertainty of future profits. Firms with more R&D ventures are riskier than others because of their R&D ventures (e.g., Berk et al., 2004); thus, it is natural for firms of high R&D intensity to have more volatile expected cash flows.

5. Gross profitability, innovative intensity, and product market competition

This section explores the interactions between product market competition, expected profitability, and innovative intensity, according to Berk, Green, and Naik (2004) and Gu (2016). In the real options model proposed by Berk et al. (2004), R&D ventures demand a higher risk premium than stochastic cash flow, because the risk of options is higher than that of underlying assets. In addition, Gu (2016) documents that this R&D premium is affected by product market competition based on the theoretical model and the R&D premium exists only in competitive industries. Therefore, to inspect the linkage between the gross profitability premium across levels of product market competition and innovation, we further conduct a portfolio analysis. First, we examine how innovative activity differs under various conditions of product market and profitability, based on simple portfolio analysis. Then, we investigate about the role of the R&D premium, which is a proxy for the innovation premium (e.g., Hou and Robinson, 2006), on the relation between competition and risk premium on expected profitability. This section attempts to dissect the risk sources of competition on expected profitability and our empirical results suggest that the market price of risk of gross (expected) profitability is significantly related to risky innovation.

5.1 R&D intensity depending on product market competition and expected profitability

Using simple double-sorting analysis, we examine the average innovative activity within double-sorted portfolios based on product market competition and gross profitability. Generally, firms in competitive industries are more likely to be engaged in innovation to maintain their profitability and competitiveness in the product markets and firms are more likely to invest in high-risk projects only if the projects yield high expected returns. Thus, the relation between gross profitability and R&D intensity may be positively related only in the competitive industries. (e.g., Gu, 2016).

For each year, we divide stocks into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of ranked values of the competition proxy in year *t* and independently divide stocks into five groups based on the ratio of gross profits to assets in year *t*. Then we calculate the average value of R&D intensity (RD/ME) for each portfolio in that year.

[Table 8 about here]

Table 8 reports the average R&D intensity for each portfolio. Panels A to C present the analysis based on *Fit_HHI*, *Fluidity*, and *Comp_HHI*, respectively. For brevity, Table 8 only reports the results of the highest and lowest terciles of the competition axis and the lowest, middle, and highest quintiles of the *GPA* axis. First, the positive R&D intensity–*GPA* relation is much stronger in the highest competition tercile and exists only in the analysis using *Fit_HHI* and *Comp_HHI*. Even though the results based on *Fluidity* are not statistically significant, the difference in R&D intensity is larger in competitive industries (high) than in concentrated industries (low). Specifically, when the analysis uses *Fit_HHI*, the high-minus-low average in innovative activities in competitive industries is 0.018, with 1% significance. In contrast, the high-minus-low average of RD/ME is even -0.002, with a t-statistic of -0.88 in concentrated industries.

5.2 Exposure to R&D premium

Using the R&D premium based on the R&D intensity measure, we examine the relation between the R&D premium and the gross profitability premium varying across levels of product market competitiveness. To measure the R&D premium, we split stocks based on NYSE breakpoints into deciles based on RD/ME and calculate the monthly value-weighted decile returns from July of year *t* to June of year *t* + 1, rebalancing the deciles in June of year *t* + 1 (e.g., Hou, Xue, and Zhang, 2015; Gu, 2016).[9] Then, using 15 (3 × 5) independently (or dependently) double-sorted portfolios based on competition and *GPA*, we calculate the value-weighted high-minus-low returns of the highest and lowest *GPA* quintile portfolios within each competition tercile and conduct alpha tests based on the following specification:

$$GPA\ premium_t = \alpha + \beta * R\&D\ premium_t + \gamma' X_t \quad \text{where } X = [MKTRF_t\ SMB_t\ HML_t\ UMD_t]'$$

The coefficient of interest is β, which is the exposure of the R&D premium. Table 9 reports the summarized results of the regression coefficients. To conserve space, we report only the coefficients of

[9] Because the accounting treatment of R&D expenses was standardized in 1975, the R&D premium data start in July 1976, which is exactly matched with our testing periods. The details are summarized in the Appendix.

the R&D premium and the difference of β between *GPA* spreads in the high and low competition terciles.

[Table 9 about here]

Panels A and B of Table 9 report the results of independent and dependent double-sorting analysis. Exposure to the R&D premium is much greater in competitive industries than in concentrated industries. For instance, when the analysis uses *Fit_HHI* as the competition proxy, exposure to the R&D premium in the highest competition level tercile is 0.20, with 1% significance, but exposure to the R&D premium in the lowest competition level tercile is -0.01, with a t-statistic of -0.12. The economic magnitude and statistical significance are much greater among firms in competitive industries and the results are robust to different sorting methods and competition measures. Overall, the empirical results imply that the risk premium on expected profitability is closely related to risky innovations (Berk, Green, and Naik, 2004; Hou and Robinson, 2006). In addition, the results of double-sorting analysis based on NYSE breakpoints are reported in the Appendix.

6. Robustness checks

In Section 3.3, we control for possible forces that are not controlled for in the portfolio analysis, such as firm size and price momentum. In this section, we additionally control for the interaction effects of information uncertainty and limits to arbitrage. Wang and Yu (2013) document a gross profitability premium primarily among firms with high arbitrage costs or high information uncertainty and find the gross profitability premium to be the result of mispricing rather than compensation for risk. The authors conduct a Fama–MacBeth (1973) regression using interaction terms to support their findings. Since the interaction effects of gross profitability with product market competition could be induced by interaction effects with information uncertainty or arbitrage costs, we should control for other potential interaction effects to check the robustness of our empirical results.

6.1 Impact of information uncertainty

To control for mispricing effects, we first control for firm information uncertainty and its interaction effects with gross profitability. There are many kinds of proxies for information uncertainty and we choose firm size because smaller firms tend to be limited in their information (e.g., Zhang, 2006). Using a similar regression specification as that of Section 3.3, we check the interaction terms between gross profitability and a high competition dummy variable.

6.2 Impact of limits to arbitrage

Another mispricing channel for the gross profitability premium is limits to arbitrage. Shleifer and Vishny (1997) argue that mispricing would not be completely traded away in situations in which there are more limits on arbitrage because arbitrage is costly. Building on this idea, we control for the interaction effects of different proxies of limits to arbitrage with gross profitability in the cross-sectional regression. We use Amihud's (2002) illiquidity measure and idiosyncratic volatility as a proxy for limits to arbitrage.

[Table 10 about here]

Table 10 reports the overall results, controlling for the interactive effects of gross profitability with information uncertainty and limits to arbitrage. Table 10 consists of nine columns, in which each set of three columns presents the results based on the analysis using three different competition measures. Almost all the interaction terms of interest are positive and statistically significant, implying that gross profitability predicts the expected stock returns more significantly in competitive industries and these interaction effects are robust to the potential mispricing channels of the gross profitability premium.

7. Conclusions

This paper attempts to resolve a puzzle in the asset pricing literature, the gross profitability premium, which is explained as a risk premium on expected profitability. In this paper, we document that product market competition might be the source of risk associated with firms' expected cash flows and propose supportive empirical evidence.

Using a conventional empirical approach with three kinds of different proxies for product market competition, this study shows that the gross profitability premium is much higher in competitive industries. Since firm productivity is threatened by market competition, firms competing in the different product markets are fundamentally different, even though they have the same expected future cash flow. Thus, investors demand higher compensation for holding productive stocks in highly competitive industries compared to stocks of similar productivity in concentrated industries.

This paper makes two main contributions. First, it contributes to the literature on dissecting the gross profitability premium. Due to the lack of empirical studies, this paper attempts to provide empirical evidence supporting the gross profitability premium being the result of compensation for risk. In addition, following Berk et al. (2004), Hou and Robinson (2006), and Gu (2016), we provide an empirical hint of the pricing mechanism behind expected profitability, which is the interaction between product market competition and innovation risk. We empirically show that the intensified profitability premium is a result of innovation risk and that innovative investments are more active among productive firms in competitive industries.

Second, this study contributes to the literature on the relation between competition and the cross section of stock returns, which reports contradicting theoretical and empirical results (e.g., Hou and Robinson, 2006; Butamante and Donangelo, 2017. In this regard, our paper finds supportive empirical results showing that firms with high expected profits show a positive competition–return relation, while firms with low expected profits exhibit a negative competition–return relation. We attribute the different relations to the different mechanisms of the risk channels of competition.

Our empirical results are robust to other driving forces of stock returns and robust to the mispricing channel of the gross profitability premium. The overall results suggest that product market structure has a significant impact on the risk of firms with higher expected profitability and could be one of the risk channels driving the gross profitability premium.

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Table 1. Descriptive statistics of the main variables

The accounting data cover fiscal years 1975 to 2016, so the final monthly sample period is from July 1976 to December 2016. Panel A presents the summary statistics of three competition proxies (*Fit_HHI*, *Fluidity*, and *Comp_HHI*) and gross profits-to-assets ratios (*GPA*). We reports the number of observations, average, standard deviation, minimum, maximum, and quartile values. Panel B reports the time series averages of the cross-sectional correlations among the four main variables. The upper triangular matrix presents the Pearson correlations and the lower triangular matrix shows the Spearman rank correlations. In this paper, we analyze the sample for different testing periods because the three kinds of competition measures cover different periods: *Fit_HHI* covers from 1975 to 2005, *Fluidity* covers from 1997 to 2015, and *Comp_HHI* covers from 1976 to 2016. Due to differences in the coverage of the competition measures, our testing period consists of three periods: July 1976 to June 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). The variables *Fit_HHI* and *Fluidity* are obtained from the Hoberg–Phillips Data Library and *Comp_HHI* is the HHI based on the Compustat Segment database merged with the Compustat database. The details of the methodology for the construction of the variables are explained in the Appendix.

	Obs	Mean	Std dev	Min	25th pctl	50th pctl	75th pctl	Max
Panel A: Summary Statistics								
Fit_HHI	1,089,017	0.060	0.020	0.035	0.046	0.054	0.068	0.179
Fluidity	687,367	6.620	3.233	1.162	4.176	6.021	8.501	21.575
Comp_HHI	1,438,377	0.233	0.182	0.041	0.101	0.180	0.295	1.000
GPA	1,706,753	0.381	0.275	-1.114	0.205	0.354	0.532	1.506
Panel B: Correlation Matrix								
	Fit_HHI	*Fluidity*	*Comp_HHI*	*GPA*				
Fit_HHI	1	-0.29	0.38	0.01				
Fluidity	-0.34	1	-0.19	-0.29				
Comp_HHI	0.43	-0.24	1	0.02				
GPA	0.01	-0.23	0.01	1				

Table 2. Univariate sorts on gross profitability and portfolio characteristics

At the end of June of each year *t*, we divide stocks into five portfolios based on *GPA* of the fiscal year *t* – 1 and these quintile portfolios are rebalanced annually at the end of June and held from July of year *t* to June of year *t* + 1. Panels A to C present the results of univariate sorts based on three different samples across different competition proxies. Panel A reports the results based on *Fit_HHI*, Panel B the results based on *Fluidity*, and Panel C the results based on *Comp_HHI*. We calculate the value-weighted (VW) and equal-weighted (EW) Carhart (1997) 4-factor four-factor alphas for the quintile portfolios and the risk-adjusted performance of high-minus-low returns. For brevity, we report only the results of the highest (Q5), middle (Q3), and the lowest (Q1) quintiles. Furthermore, we report the average characteristics (book-to-market ratio, RD/ME, and competition proxy) of each quintile portfolio. In this paper, we analyze the sample for different testing periods because the three kinds of competition measures cover different periods: *Fit_HHI* covers from 1975 to 2005, *Fluidity* covers from 1997 to 2015, and *Comp_HHI* covers from 1976 to 2016. Due to differences in the coverage of the competition measures, our testing period consists of three periods: July 1976 to June 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey–West (1987) adjusted and in parentheses. The important empirical results are expressed in bold.

	VW	EW	log(BM)	RD/ME	Competition
Panel A: July 1976 to June 2007 (Competition Proxy = Fit_HHI)					
Q1	-0.14	-0.23	-0.646	0.024	0.061
	(-0.93)	(-1.50)			
Q3	0.15	0.12	-0.638	0.026	0.063
	(1.62)	(1.29)			
Q5	0.26	0.40	-1.050	0.024	0.062
	(2.52)	(2.85)			
Q5 – Q1	**0.41**	**0.63**	-0.404	0.000	0.001
	(1.90)	**(3.91)**	(-9.05)	(0.07)	(1.00)
Panel B: July 1998 to December 2016 (Competition Proxy = Fluidity)					
Q1	-0.24	-0.28	-0.788	0.033	8.654
	(-1.67)	(-1.57)			
Q3	0.22	0.20	-0.816	0.026	6.008
	(1.92)	(1.51)			
Q5	0.25	0.43	-1.246	0.024	5.753
	(2.07)	(2.52)			
Q5 – Q1	**0.49**	**0.71**	-0.458	-0.009	-2.902
	(2.26)	**(3.09)**	(-6.88)	(-2.81)	(-14.76)
Panel C: July 1977 to December 2016 (Competition Proxy = Comp_HHI)					
Q1	-0.15	-0.26	-0.646	0.024	0.252
	(-1.19)	(-2.09)			
Q3	0.16	0.11	-0.638	0.026	0.243
	(1.97)	(1.45)			
Q5	0.29	0.37	-1.050	0.024	0.250
	(3.10)	(3.23)			
Q5 – Q1	**0.44**	**0.63**	-0.404	0.000	-0.002
	(2.34)	**(4.26)**	(-9.05)	(0.07)	(-0.31)

Table 3. Independent double sorts on gross profitability and competition

At the end of June of each year *t*, we divide stocks into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of ranked values of the competition proxy in year *t* – 1 and independently divide stocks into five groups based on gross profits to assets in year *t* – 1. The portfolios are rebalanced annually at the end of June. We reports two kinds of weighting schemes, value weighted (VW) and equal weighted (EW), and both the mean excess returns and Carhart (1997) 4-factor risk-adjusted alphas. Panels A to C report the average returns on the periods covered with *Fit_HHI*, *Fluidity*, and *Comp_HHI*, respectively. Since *Fit_HHI* and *Comp_HHI* decrease as product market competition intensifies, the low (high) competition columns presents the highest (lowest) terciles based on the corresponding competition proxy. In contrast, the low (high) competition columns present the lowest (highest) terciles based on *Fluidity*. The last columns report the differences of the average excess returns and risk-adjusted returns of the high and low competition terciles. Due to differences in the coverage of the competition measures, our testing period consists of three periods: July 1976 to June 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey–West (1987) adjusted and in parentheses. The important empirical results are expressed in bold.

	Low competition				High competition				High - Low			
	GPA1	GPA3	GPA5	5 - 1	GPA1	GPA3	GPA5	5 - 1	GPA1	GPA3	GPA5	5 - 1
Panel A. Competition Proxy = Fit_HHI												
Exess returns (VW)	0.55	0.81	0.71	**0.16**	-0.06	0.36	1.05	**1.11**	-0.61	-0.45	0.34	**0.95**
	(1.79)	(2.96)	(2.38)	**(0.57)**	(-0.12)	(0.92)	(2.55)	**(3.08)**	(-1.52)	(-1.42)	(0.98)	**(2.34)**
Exess returns (EW)	0.38	0.89	0.93	**0.55**	0.21	0.76	1.52	**1.31**	-0.17	-0.12	0.59	**0.76**
	(1.00)	(2.50)	(2.59)	**(3.25)**	(0.40)	(1.81)	(3.17)	**(5.02)**	(-0.50)	(-0.52)	(1.97)	**(3.08)**
Alphas (VW)	-0.05	0.15	0.12	**0.17**	-0.79	-0.23	0.45	**1.24**	-0.74	-0.38	0.33	**1.07**
	(-0.24)	(1.05)	(0.68)	**(0.58)**	(-2.77)	(-0.99)	(2.36)	**(3.60)**	(-2.24)	(-1.41)	(1.17)	**(2.62)**
Alphas (EW)	-0.34	0.10	0.14	**0.48**	-0.23	0.16	1.01	**1.23**	0.11	0.06	0.87	**0.76**
	(-1.83)	(0.69)	(0.73)	**(2.80)**	(-0.70)	(0.76)	(3.21)	**(4.97)**	(0.41)	(0.27)	(2.87)	**(2.97)**
Panel B. Competition Proxy = Fluidity												
Exess returns (VW)	0.90	0.60	0.48	**-0.42**	0.30	0.66	1.10	**0.80**	-0.60	0.06	0.63	**1.23**
	(1.58)	(1.75)	(1.57)	**(-1.09)**	(0.51)	(1.33)	(1.98)	**(1.82)**	(-1.38)	(0.14)	(1.20)	**(2.40)**
Exess returns (EW)	0.85	1.04	1.19	**0.34**	0.58	1.15	1.63	**1.05**	-0.27	0.11	0.44	**0.71**
	(1.36)	(1.97)	(2.38)	**(1.32)**	(0.78)	(1.98)	(2.27)	**(3.13)**	(-0.54)	(0.28)	(0.76)	**(1.98)**
Alphas (VW)	0.22	0.09	0.11	**-0.11**	-0.38	0.35	0.63	**1.00**	-0.60	0.25	0.51	**1.11**
	(0.72)	(0.54)	(0.69)	**(-0.33)**	(-1.93)	(1.52)	(1.97)	**(2.49)**	(-1.45)	(0.81)	(1.34)	**(2.18)**

Alphas (EW)	-0.11	0.17	0.40	**0.51**	-0.31	0.37	0.87	**1.18**	-0.20	0.20	0.47	**0.67**
	(-0.55)	(0.99)	(2.09)	**(2.15)**	(-1.30)	(2.24)	(2.86)	**(3.61)**	(-0.62)	(0.87)	(1.30)	**(1.86)**
Panel C. Competition Proxy = Comp_HHI												
Exess returns (VW)	0.46	0.45	0.57	**0.10**	0.23	0.59	0.86	**0.63**	-0.23	0.14	0.29	**0.52**
	(1.83)	(1.80)	(2.22)	**(0.46)**	(0.66)	(2.13)	(3.16)	**(2.59)**	(-0.94)	(0.78)	(1.48)	**(1.72)**
Exess returns (EW)	0.35	0.86	1.02	**0.68**	0.26	0.90	1.33	**1.07**	-0.09	0.03	0.31	**0.40**
	(0.84)	(2.57)	(3.08)	**(3.71)**	(0.58)	(2.38)	(3.19)	**(4.54)**	(-0.52)	(0.19)	(1.36)	**(1.76)**
Alphas (VW)	0.00	-0.04	0.13	**0.13**	-0.27	0.18	0.59	**0.86**	-0.27	0.22	0.46	**0.74**
	(0.00)	(-0.35)	(1.01)	**(0.64)**	(-1.74)	(1.50)	(4.44)	**(3.83)**	(-1.47)	(1.34)	(2.52)	**(2.75)**
Alphas (EW)	-0.42	0.07	0.28	**0.70**	-0.42	0.20	0.80	**1.22**	0.00	0.13	0.52	**0.52**
	(-2.38)	(0.58)	(2.04)	**(4.19)**	(-2.00)	(1.55)	(3.27)	**(5.51)**	(-0.01)	(1.01)	(2.38)	**(2.38)**

Table 4. Dependent double sorts on gross profitability and competition

At the end of June of each year *t*, we divide stocks into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of ranked values of the competition proxy in year *t* – 1 and dependently divide stocks into five groups based on gross profits to assets in year *t* – 1. The portfolios are rebalanced annually at the end of June. We reports two kinds of weighting schemes, value weighted (VW) and equal weighted (EW), and both the mean excess returns and Carhart (1997) 4-factor risk-adjusted alphas. Panels A to C report the average returns on the periods covered with *Fit_HHI*, *Fluidity*, and *Comp_HHI*, respectively. Since *Fit_HHI* and *Comp_HHI* decrease as product market competition intensifies, the low (high) competition columns presents the highest (lowest) terciles based on the corresponding competition proxy. In contrast, the low (high) competition columns present the lowest (highest) terciles based on *Fluidity*. The last columns report the differences of the average excess returns and risk-adjusted returns of the high and low competition terciles. Due to differences in the coverage of the competition measures, our testing period consists of three periods: July 1976 to June 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey–West (1987) adjusted and in parentheses. The important empirical results are expressed in bold.

	Low competition				High competition				High - Low			
	GPA1	GPA3	GPA5	5 - 1	GPA1	GPA3	GPA5	5 - 1	GPA1	GPA3	GPA5	5 - 1
Panel A. Competition Proxy = Fit_HHI												
Exess returns (VW)	0.51	0.79	0.70	**0.19**	-0.01	0.55	1.21	**1.22**	-0.51	-0.23	0.51	**1.03**
	(1.71)	(2.87)	(2.38)	**(0.73)**	(-0.01)	(1.48)	(2.59)	**(2.95)**	(-1.12)	(-0.83)	(1.19)	**(2.25)**
Exess returns (EW)	0.47	0.89	0.89	**0.42**	0.22	0.76	1.53	**1.31**	-0.25	-0.13	0.63	**0.88**
	(1.26)	(2.52)	(2.51)	**(2.75)**	(0.40)	(1.80)	(3.18)	**(4.68)**	(-0.67)	(-0.55)	(2.12)	**(3.48)**
Alphas (VW)	-0.11	0.11	0.11	**0.22**	-0.79	0.06	0.62	**1.41**	-0.68	-0.05	0.51	**1.19**
	(-0.57)	(0.76)	(0.63)	**(0.78)**	(-2.45)	(0.30)	(2.84)	**(3.66)**	(-1.86)	(-0.19)	(1.65)	**(2.69)**
Alphas (EW)	-0.30	0.11	0.10	**0.40**	-0.21	0.15	1.01	**1.22**	0.08	0.05	0.91	**0.82**
	(-1.75)	(0.72)	(0.56)	**(2.57)**	(-0.61)	(0.73)	(3.16)	**(4.62)**	(0.27)	(0.21)	(2.99)	**(3.27)**
Panel B. Competition Proxy = Fluidity												
Exess returns (VW)	0.87	0.71	0.49	**-0.38**	0.53	0.55	1.02	**0.49**	-0.34	-0.16	0.53	**0.87**
	(1.59)	(1.87)	(1.52)	**(-1.03)**	(0.66)	(1.07)	(2.26)	**(0.90)**	(-0.57)	(-0.40)	(1.29)	**(1.73)**
Exess returns (EW)	0.93	1.06	1.11	**0.18**	0.73	0.95	1.51	**0.77**	-0.20	-0.11	0.39	**0.59**
	(1.55)	(2.12)	(2.18)	**(0.74)**	(0.86)	(1.51)	(2.16)	**(2.34)**	(-0.29)	(-0.29)	(0.70)	**(1.62)**
Alphas (VW)	0.12	0.32	0.10	**-0.03**	-0.17	-0.02	0.62	**0.79**	-0.29	-0.34	0.53	**0.82**
	(0.51)	(1.44)	(0.53)	**(-0.10)**	(-0.53)	(-0.10)	(2.37)	**(1.87)**	(-0.66)	(-1.02)	(1.53)	**(1.72)**

Alphas (EW)	-0.02	0.23	0.35	**0.37**	-0.24	0.18	0.74	**0.98**	-0.21	-0.05	0.40	**0.61**
	(-0.11)	(1.31)	(1.69)	**(1.57)**	(-0.83)	(0.87)	(2.66)	**(3.25)**	(-0.56)	(-0.19)	(1.15)	**(1.76)**
Panel C. Competition Proxy = Comp_HHI												
Exess returns (VW)	0.51	0.44	0.56	**0.05**	0.29	0.58	0.83	**0.54**	-0.22	0.14	0.27	**0.49**
	(1.84)	(1.78)	(2.10)	**(0.25)**	(0.82)	(2.20)	(3.03)	**(2.27)**	(-0.94)	(0.85)	(1.29)	**(1.74)**
Exess returns (EW)	0.36	0.87	1.01	**0.64**	0.29	0.75	1.31	**1.02**	-0.08	-0.11	0.30	**0.38**
	(0.93)	(2.61)	(3.03)	**(4.11)**	(0.60)	(2.02)	(3.11)	**(4.24)**	(-0.38)	(-0.72)	(1.32)	**(1.81)**
Alphas (VW)	-0.02	-0.03	0.13	**0.15**	-0.24	0.19	0.58	**0.81**	-0.21	0.21	0.45	**0.66**
	(-0.16)	(-0.24)	(1.01)	**(0.76)**	(-1.44)	(1.34)	(4.32)	**(3.57)**	(-1.04)	(1.21)	(2.39)	**(2.40)**
Alphas (EW)	-0.44	0.13	0.28	**0.71**	-0.38	0.05	0.77	**1.15**	0.06	-0.08	0.49	**0.43**
	(-2.76)	(0.94)	(1.97)	**(4.67)**	(-1.66)	(0.43)	(3.18)	**(5.20)**	(0.32)	(-0.57)	(2.32)	**(2.20)**

Table 5. Fama–MacBeth regressions of excess returns on measures of competition

This table presents the results of Fama–MacBeth (1973) cross-sectional regressions. Our regression specification is

$$Excess\ Return_{i,t+1} = \alpha + \beta_0 GPA_{i,t} + \beta_1 HighCompetition_t + \beta_2 GPA_{i,t} HighCompetition_t + Controls_{i,t} + \epsilon_{i,t+1}$$

where $Excess\ Return_{i,t+1}$ is the excess return of stock *i* in month *t* + 1, $GPA_{i,t}$ is the gross profitability of firm *i* in month *t*, $HighCompetition_t$ is a dummy variable indicating that firm *i* is operating in the top 30% of ranked value of product market competitiveness at month *t*, and $Controls_{i,t}$ includes firm size, the book-to-market ratio, the past month's returns, the past 11 months of returns skipping one month, idiosyncratic volatility, illiquidity, and R&D intensity. The descriptions of the variable constructions are in the Appendix. All the independent variables are trimmed at the 1% and 99% levels. Due to differences in the coverage of the competition measures, our testing period consists of three periods: July 1976 to June 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey–West (1987) adjusted and in parentheses. The important empirical results are expressed in bold.

	Slope of coefficients and t-statistics from cross-sectional regression of excess returns on competition and firm characteristics.								
	Competition Proxy = *Fit_HHI*			Competition Proxy = *Fluidity*			Competition Proxy = *Comp_HHI*		
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.57	0.72	0.78	0.57	0.37	0.80	0.51	0.55	0.71
	(1.55)	(2.39)	(2.88)	(1.16)	(0.83)	(2.03)	(1.47)	(1.91)	(2.74)
GPA	0.71	0.74	0.85	0.61	0.82	0.74	0.71	0.80	0.90
	(3.07)	(3.14)	(3.85)	(2.19)	(3.01)	(2.76)	(3.92)	(4.39)	(4.98)
Dummy(High)	-0.33	-0.27	-0.28	-0.14	-0.08	-0.06	-0.14	-0.10	-0.09
	(-2.05)	(-1.83)	(-1.89)	(-0.51)	(-0.36)	(-0.28)	(-1.14)	(-0.95)	(-0.87)
GPA*Dummy(High)	**0.71**	**0.58**	**0.56**	**0.52**	**0.61**	**0.48**	**0.51**	**0.60**	**0.49**
	(2.57)	**(2.36)**	**(2.37)**	**(1.93)**	**(1.72)**	**(1.37)**	**(2.04)**	**(2.78)**	**(2.41)**
log(ME)		0.00	-0.24		0.01	-0.11		0.03	-0.20
		(-0.02)	(-5.52)		(0.30)	(-2.50)		(0.63)	(-5.49)
log(BM)		0.46	0.49		0.25	0.20		0.41	0.44
		(4.19)	(4.76)		(1.93)	(1.57)		(4.61)	(5.02)
REV		-0.04	-0.05		-0.02	-0.02		-0.04	-0.04
		(-8.38)	(-9.64)		(-2.88)	(-3.45)		(-8.10)	(-9.01)
MOM		0.99	0.76		0.11	0.08		0.66	0.44
		(4.25)	(3.51)		(0.20)	(0.16)		(2.34)	(1.65)
IVOL			-0.12			-0.20			-0.15
			(-2.56)			(-2.71)			(-3.72)
Amihud			0.11			0.48			0.11
			(7.48)			(5.31)			(8.80)
RD/ME			2.10			2.79			1.93
			(2.15)			(1.90)			(2.66)
# Obs	1,014,120	918,897	823,490	513,100	450,240	437,104	1,544,590	1,301,536	1,181,045
R^2	0.005	0.035	0.048	0.012	0.047	0.058	0.005	0.033	0.045

Table 6. Industry competition and dispersion of gross profitability

This table presents the relation between industry-level competition and the dispersion of profitability. Panel A reports the correlation matrix of two kinds of industry-level competition (*Fit_HHI* and *Comp_HHI*) and the contemporaneous and future dispersion of gross profitability within the same industry. Panel B reports the estimated coefficients of the predictive regression of the future dispersion of gross profitability on current industry-level production market competition. We control for past industry-level profitability and report t-statistics based on two-way clustered standard errors to control for time and industry fixed effects.

Panel A. Time-series Average of Cross-sectional Correlations

	Fit_HHI(t)	*Comp_HHI(t)*	*GP_DISP(t)*	*GP_DISP(t+1)*	*GP_DISP(t+2)*	*GP_DISP(t+3)*
Fit_HHI(t)	1	0.400	-0.090	**-0.091**	**-0.081**	**-0.083**
		(13.95)	(-6.87)	**(-7.95)**	**(-6.02)**	**(-6.89)**
Comp_HHI(t)		1	-0.074	**-0.051**	**-0.045**	**-0.046**
			(-6.96)	**(-4.36)**	**(-4.14)**	**(-4.26)**
GP_DISP(t)			1	0.542	0.467	0.428
				(25.34)	(22.63)	(21.62)
GP_DISP(t+1)				1	0.538	0.466
					(24.86)	(21.73)
GP_DISP(t+2)					1	0.540
						(24.60)
GP_DISP(t+3)						1

Panel B. Predictive Regression Coefficients

	Regress on *Fit_HHI(t)*	Regress on *Comp_HHI(t)*
GP_DISP(t+1)	**-0.505**	**-0.084**
	(-5.84)	**(-7.55)**
GP_DISP(t+2)	**-0.481**	**-0.084**
	(-5.62)	**(-7.63)**
GP_DISP(t+3)	**-0.535**	**-0.083**
	(-6.63)	**(-8.00)**

Table 7. Fama–MacBeth regressions of the future volatility of gross profitability on measures of competition

This table presents the results of Fama–MacBeth (1973) cross-sectional regressions. Our regression specification is

$$Vol(GP)_{i,t+1\sim t+k} = \alpha + \beta_0 vol(GP)_{i,t} + \beta_1 Competition_{i,t} + \beta_2 \log(ME_{i,t}) + \beta_3 \frac{RD_{i,t}}{ME_{i,t}} + \beta_4 IVOL_{i,t} + \beta_5 GPA_{i,t} + \epsilon_{i,t+1}$$

$$where\ k \in \{2,3,4\}$$

where $Vol(GP)_{i,t+1\sim t+k}$ is the future volatility of the gross profitability of firm *i* in years *t* + 1 to *t* + *k* and $Competition_{i,t}$ is one of the three kinds of competition measures. We control for firm size, firm R&D intensity, firm-specific idiosyncratic risk, and current gross profitability, which could affect the future volatility of profitability. We also control for non-overlapping lagged *GPA* volatility to erase an autoregressive component of the dependent variable and independent variables are trimmed at the 1% and 99% levels. Due to differences in the coverage of the competition measures, our testing period consists of three periods: July 1976 to June 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey–West (1987) adjusted and in parentheses. The important empirical results are expressed in bold.

	Slope of coefficients and t-statistics from cross-sectional regressions of from future earnings volatility on competition and firm characteristics.					
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. 2-year volatility						
Intercept	1.35	0.57	1.10	0.18	-0.25	0.18
	(11.66)	(6.52)	(16.73)	(3.23)	(-2.85)	(4.94)
Lag(VOL)	0.58	0.59	0.60	0.47	0.50	0.49
	(46.69)	(33.24)	(49.56)	(38.76)	(25.43)	(35.47)
Fit_HHI	**-4.38**			**-1.20**		
	(-4.23)			**(-1.55)**		
Fluidity		**0.08**			**0.07**	
		(7.25)			**(5.76)**	
Comp_HHI			**-0.26**			**-0.14**
			(-3.02)			**(-2.05)**
log(ME)				-0.04	-0.04	-0.04
				(-4.21)	(-2.56)	(-5.31)
RD/ME				0.77	1.33	1.31
				(3.25)	(6.25)	(4.24)
IVOL				0.19	0.21	0.20
				(9.26)	(10.14)	(12.28)
GPA				1.08	0.78	0.91
				(13.12)	(5.79)	(8.15)
# Obs	105,629	47,127	152,637	101,030	44,922	145,944
R^2	0.330	0.332	0.343	0.378	0.368	0.389
Panel B. 3-year volatility						
Intercept	1.66	0.62	1.34	0.29	-0.19	0.24
	(12.53)	(6.83)	(16.98)	(3.92)	(-1.89)	(5.23)
Lag(VOL)	0.58	0.61	0.61	0.45	0.50	0.49
	(53.31)	(27.64)	(44.82)	(41.16)	(20.59)	(31.76)
Fit_HHI	**-6.10**			**-2.20**		
	(-4.84)			**(-2.38)**		

Fluidity		**0.11**			**0.09**	
		(10.72)			**(8.46)**	
Comp_HHI			**-0.45**			**-0.28**
			(-3.94)			**(-3.40)**
log(ME)				-0.04	-0.06	-0.05
				(-3.16)	(-4.02)	(-4.85)
RD/ME				1.17	1.79	1.72
				(4.41)	(7.76)	(5.53)
IVOL				0.25	0.23	0.25
				(10.65)	(7.96)	(12.67)
GPA				1.14	0.79	0.98
				(10.65)	(4.85)	(7.42)
# Obs	92,563	41,466	131,491	88,562	39,564	125,814
R^2	0.326	0.311	0.328	0.372	0.373	0.389
Panel C. 4-year volatility						
Intercept	1.87	0.69	1.50	0.41	-0.13	0.32
	(14.10)	(7.76)	(18.34)	(4.64)	(-0.92)	(5.58)
Lag(VOL)	0.58	0.60	0.61	0.45	0.49	0.48
	(63.74)	(28.72)	(43.83)	(43.14)	(22.68)	(32.35)
Fit_HHI	**-7.03**			**-2.76**		
	(-5.30)			**(-2.77)**		
Fluidity		**0.12**			**0.09**	
		(9.91)			**(4.32)**	
Comp_HHI			**-0.52**			**-0.30**
			(-3.90)			**(-2.98)**
log(ME)				-0.04	-0.07	-0.05
				(-2.65)	(-3.60)	(-4.33)
RD/ME				1.46	2.78	2.36
				(5.51)	(4.16)	(5.43)
IVOL				0.28	0.26	0.28
				(11.00)	(7.17)	(12.15)
GPA				1.11	0.71	0.97
				(7.71)	(3.99)	(6.24)
# Obs	81,635	36,905	113,774	78,084	35,250	108,862
R^2	0.317	0.301	0.314	0.369	0.376	0.387

Table 8. Average R&D intensity of independent double-sorted portfolios by competition and gross profitability

For each year, we divide stocks into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of ranked values of the competition proxy in year *t* and independently divide stocks into five groups based on gross profits to assets in year *t*. Then we calculate the average value of R&D intensity (RD/ME) for each portfolio in the contemporaneous year. Panels A to C present the analysis based on *Fit_HHI*, *Fluidity*, and *Comp_HHI*, respectively. For brevity, this table reports only the results of the highest and lowest terciles of the competition axis and the lowest, middle, and highest quintiles of the *GPA* axis. Due to differences in the coverage of the competition measures, our testing period consists of three periods: July 1976 to June 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey–West (1987) adjusted and in parentheses. The important empirical results are expressed in bold.

	GPA1	GPA3	GPA5	GPA5 - GPA1
Competition Level				
Panel A. Competition Proxy = Fit_HHI				
Low	0.021	0.027	0.019	**-0.002**
				(-0.88)
High	0.022	0.025	0.040	**0.018**
				(5.69)
High - Low	0.001	-0.002	**0.021**	**0.019**
	(0.20)	(-0.47)	**(2.83)**	**(7.62)**
Panel B. Competition Proxy = Fluidity				
Low	0.011	0.019	0.014	**0.002**
				(0.85)
High	0.048	0.033	0.052	**0.003**
				(1.38)
High - Low	0.037	0.014	**0.038**	**0.001**
	(7.65)	(4.49)	**(9.07)**	**(1.34)**
Panel C. Competition Proxy = Comp_HHI				
Low	0.014	0.021	0.013	**-0.001**
				(-0.68)
High	0.022	0.029	0.039	**0.018**
				(5.84)
High - Low	0.007	0.008	**0.026**	**0.019**
	(1.65)	(3.24)	**(6.33)**	**(6.19)**

Table 9. Exposure to the R&D premium

This table reports the summarized results of the regression coefficients as follows:

$$GPA\ premium_t = \alpha + \beta * R\&D\ premium_t + \gamma' X_t \quad where\ X = [MKTRF_t\ SMB_t\ HML_t\ UMD_t]'$$

To measure the R&D premium, we split stocks based on the NYSE breakpoints into deciles based on RD/ME and calculate monthly value-weighted decile returns from July of year *t* to June of year *t* + 1, rebalancing deciles in June of year *t* + 1. Then, using 15 (3 × 5) independently (or dependently) double-sorted portfolios based on competition and *GPA*, we calculate the value-weighted high-minus-low returns of the highest and lowest *GPA* quintile portfolios within each competition tercile and conduct an alpha test based on the above regression specification. To conserve space, we report only the coefficients of the R&D premium (β) and the differences of β between *GPA* spreads in the high and low competition terciles. Due to differences in the coverage of the competition measures, our testing period consists of three periods: July 1976 to une 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey–West (1987) adjusted and in parentheses. The important empirical results are expressed in bold..

	Competition Level			
Competition Proxy	High	Middle	Low	High - Low
Panel A. Independent sorted portfolios				
Fit_HHI	**0.20**	0.02	-0.01	**0.21**
	(3.38)	(0.30)	(-0.12)	**(2.17)**
Fluidity	**0.30**	0.00	-0.04	**0.35**
	(3.83)	(-0.05)	(-0.70)	**(3.18)**
Comp_HHI	**0.09**	0.05	-0.07	**0.16**
	(1.90)	(0.93)	(-1.15)	**(2.50)**
Panel B. Dependent sorted portfolios				
Fit_HHI	**0.29**	0.04	-0.01	**0.30**
	(3.83)	(0.70)	(-0.14)	**(2.52)**
Fluidity	**0.10**	-0.02	-0.08	**0.18**
	(1.36)	(-0.21)	(-1.24)	**(1.97)**
Comp_HHI	**0.10**	0.08	-0.04	**0.15**
	(2.00)	(1.38)	(-0.90)	**(2.51)**

Table 10. Fama–MacBeth regressions of excess returns on measures of competition and limits to arbitrage/uncertainty proxies

This table presents the results of Fama–MacBeth (1973) cross-sectional regressions. Our regression specification is

$$Excess\ Return_{i,t+1} = \alpha + \beta_0 GPA_{i,t} + \beta_1 HighCompetition_t + \beta_2 GPA_{i,t} HighCompetition_t$$
$$+\beta_3 Proxy_{i,t} + beta_4 GPA_{i,t} * Proxy_{i,t} + \gamma' Controls_{i,t} + \epsilon_{i,t+1}$$

where $Excess\ Return_{i,t+1}$ is the excess return of stock *i* in month *t* + 1, $GPA_{i,t}$ is the gross profitability of firm *i* in month *t*, $HighCompetition_t$ is a dummy variable indicating that firm *i* is in the top 30% of firms of ranked value of product market competitiveness at month *t*, and $Controls_{i,t}$ include the book-to-market ratio, the past month's returns, and the past 11 months of returns skipping one month. The term $Proxy_{i,t}$ is an information uncertainty/limits to arbitrage measure and we add interaction terms with $GPA_{i,t}$. The descriptions of the variable constructions are in the Appendix. All the independent variables are trimmed at the 1% and 99% levels. Due to differences in the coverage of the competition measures, our testing period consists of three periods: July 1976 to June 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey–West (1987) adjusted and in parentheses. The important empirical results are expressed in bold.

	Slope of coefficients and t-statistics from the cross-sectional regression of excess returns on competition and firm characteristics.								
	Competition Proxy = *Fit_HHI*			Competition Proxy = *Fluidity*			Competition Proxy = *Comp_HHI*		
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.72	0.67	1.11	0.37	0.46	0.93	0.72	0.67	1.11
	(2.39)	(2.19)	(3.91)	(0.83)	(1.01)	(2.37)	(2.39)	(2.19)	(3.91)
GPA	0.74	0.82	0.37	0.82	0.83	0.26	0.74	0.82	0.37
	(3.13)	(3.24)	(1.67)	(3.01)	(2.89)	(0.84)	(3.13)	(3.24)	(1.67)
Dummy(High)	-0.27	-0.29	-0.23	-0.08	-0.11	0.04	-0.27	-0.29	-0.23
	(-1.84)	(-1.86)	(-1.51)	(-0.35)	(-0.50)	(0.22)	(-1.84)	(-1.86)	(-1.51)
GPA*Dummy(High)	**0.58**	**0.59**	**0.52**	**0.60**	**0.60**	**0.41**	**0.58**	**0.59**	**0.52**
	(2.38)	**(2.35)**	**(2.10)**	**(1.72)**	**(1.67)**	**(1.20)**	**(2.38)**	**(2.35)**	**(2.10)**
*GPA*1/log(ME)*	0.00			0.00			0.00		
	(1.30)			(-0.66)			(1.30)		
*GPA*Amihud*		0.01			-0.16			0.01	
		(0.58)			(-0.52)			(0.58)	
*GPA*IVOL*			0.09			0.23			0.09
			(1.73)			(2.44)			(1.73)
log(ME)	0.00	-0.23	-0.06	0.01	-0.07	-0.04	0.00	-0.23	-0.06
	(-0.03)	(-3.99)	(-1.60)	(0.31)	(-1.42)	(-0.89)	(-0.03)	(-3.99)	(-1.60)
Amihud		0.12			0.39			0.12	
		(6.82)			(2.31)			(6.82)	
IVOL			-0.19			-0.28			-0.19
			(-3.76)			(-3.21)			(-3.76)
log(BM)	0.46	0.54	0.41	0.25	0.26	0.20	0.46	0.54	0.41
	(4.20)	(5.00)	(4.17)	(1.93)	(2.02)	(1.67)	(4.20)	(5.00)	(4.17)
REV	-0.04	-0.05	-0.05	-0.02	-0.02	-0.02	-0.04	-0.05	-0.05
	(-8.39)	(-8.81)	(-8.90)	(-2.88)	(-2.91)	(-3.28)	(-8.39)	(-8.81)	(-8.90)
MOM	0.99	0.80	0.92	0.11	0.06	0.15	0.99	0.80	0.92
	(4.26)	(3.36)	(4.18)	(0.20)	(0.11)	(0.29)	(4.26)	(3.36)	(4.18)

# Obs	918,897	831,792	903,005	450,240	441,695	444,580	1,301,536	1,192,845	1,279,493
R^2	0.035	0.041	0.041	0.047	0.049	0.052	0.035	0.041	0.041

Appendix

Table A1. Variable definitions

Variable	Definition
Industry-Level Variables	
Fit_HHI	The fitted HHI is calculated by the two-step procedure proposed by Hoberg and Phillips (2010). First, for the subsample of manufacturing industries where actual HHIs including both public and private firms exist in the Herfindahl data from the Department of Commerce, Hoberg and Phillips (2010) regress actual industry HHI values on Compustat-based public-firm-only HHI values, the average number of employees per firm from BLS data (including both public and private firms), and the number of employees per firm from Compustat data (including only public firms). In addition, the interaction variables of each of the firm size variables with HHI from Compustat are included. In the second step, using the coefficient estimates from the first-step regression, the fitted HHI is computed for all the industries in each year. Whereas the correlation between the Compustat HHIs using segment data and the actual HHIs obtained from the Department of Commerce for manufacturing industries is only 34.1%, the correlation between actual HHIs and these fitted HHIs is 54.2% (Hoberg and Phillips, 2010). This fitted HHI variable is easily obtained from the Hoberg–Phillips Data Library.
Comp_HHI	The Compustat-based HHI is defined as the sum of squared market shares within each industry: $$HHI_{jt} = \sum_{i=1}^{N_j} s_{ijt}^2$$ where s_{ijt} is market share of firm *i* in industry *j* in year *t* and N_j is the number of firms operating in the industry *j* in year *t*. Based on the primary segment sales of each firm and the primary industry classification, the market share of an individual firm is computed by using its net sales divided by the total sales of the entire industry. All firms with non-missing sales values are included in the sample to calculate the HHI for each industry. We use the CRSP's three-digit SIC code to classify the industry of all the firms. The details of the data construction process are as follows. 1. We delete firms incorporated outside the United States because firms operating outside the United States are likely to face a different product market. 2. Data on net sales (item SALES) and valid primary four-digit SIC codes (item SIC1) are obtained from the Compustat Segment database. Segments with identical SIC codes for the same firm are aggregated into a single quantity. 3. We merge the segment data with the Compustat annual data. Firms without segment information are treated as having a single segment. 4. We calculate the industry-wide HHI and assign an industry HHI to each firm. 5. If a firm has multiple business segments, the segment with the same four-digit SIC code as the CRSP SIC code is identified as the primary segment. If none of the segments has the same SIC code as the firm, then the segment with the greatest sales is treated as the primary segment.

GP_DISP	The standard deviation of *GPA* (Gross profits-to-assets) within the same industry in the same year *t*. We classify all stocks in the sample into an industry based on the three-digit SIC code from CRSP.

Firm-Level Variables

Fluidity	Fluidity is calculated as the cosine similarity between a firm's products and changes in the products of competitors in that firm's product markets. It is updated annually and is a measure of how intensively the product market is changing around a firm each year. Greater fluidity indicates greater product market threats. Details are available from Hoberg, Phillips, and Prabhala (2014). This fitted HHI variable is easily obtained from the Hoberg–Phillips Data Library.
GPA	Gross profits to assets, calculated as total revenue (Compustat annual item REVT) minus the cost of goods sold (item COGS), divided by lagged total assets (item AT), following Novy-Marx (2013).
RD/ME	The ratio of R&D expenses to market equity, which is R&D expenses (Compustat annual item XRD) for the fiscal year ending in calendar year t divided by the market equity (from the CRSP) at the end of December of year t. The R&D premium used in this paper is constructed as follows. At the end of June of each year t, all common stocks are divided into 10 groups based on NYSE breakpoints based on the RD/ME values of calendar year t – 1. Using only firms with positive R&D expenses, we calculate the return spreads between the highest and lowest RD/ME deciles. Because the accounting disclosure of R&D expenses was standardized in 1975, data for the R&D premium defined through the RD/ME decile start in July 1976.
Vol(GP)	The standard deviation of *GPA* (gross profits-to-assets) of each firm. We calculate three versions of volatilities varying across the horizons; 2-, 3-, and 4-year. We do not calculate the volatility if there is at least one missing GPA within the horizon.
log(ME)	The logarithm of market capitalization, which is price per share (CRSP item PRC) multiplied by the number of shares outstanding (CRSP item SHROUT) of equity at the end of June of each year.
log(BM)	The logarithm of book-to-market ratio. Following Fama and French (1993), book-to-market ratio is the book equity at the end of fiscal year *t - 1* divided market equity at the end of December of year *t - 1*. Book equity is shareholder equity, plus deferred taxes, minus preferred stock, if available. Shareholder equity is as given
MOM	Cumulative stock returns over the previous 12-month skipping one-month at the end of each month.
REV	The past 1-month stock returns

IVOL	The standard deviation of residuals from regressions of daily excess stock returns on Fama-French (1993) three-factor within the past 1-month.
Amihud	Illiquidity measure proposed by Amihud (2002) is the average of ratios of absolute change of daily stock price to trading amount for the past 1-year.

Table A2. Univariate sorts on gross profitability (NYSE breakpoints)

At the end of June of each year *t*, we divide stocks into five portfolios based on NYSE breakpoints *GPA* of the fiscal year *t* – 1 and these quintile portfolios are rebalanced annually at the end of June and held from July of year *t* to June of year *t* + 1. Six columns present the results of univariate sorts based on three different samples across different competition proxies. The first two columns report the results based on *Fit_HHI*, The subsequent two columns exhibit the results based on *Fluidity*, and the last two columns present the results based on *Comp_HHI*. We calculate the value-weighted (VW) and equal-weighted (EW) Carhart (1997) 4-factor four-factor alphas for the quintile portfolios and the risk-adjusted performance of high-minus-low returns. In this paper, we analyze the sample for the different testing periods because three kinds of competition measures cover different periods. *Fit_HHI* covers from 1975 to 2005, *Fluidity* covers from 1997 to 2015, and *Comp_HHI* covers from 1976 to 2016. Due to different coverage of competition measures, our testing periods consist of three kinds of period; July 1976 – June 2007 (sample with *Fit_HHI*), July 1998 – December 2016 (sample with *Fluidity*), and July 1977 – December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey–West (1987) adjusted and in parentheses. The important empirical results are expressed in bold.

GPA	1976 - 2007		1998 - 2016		1977 - 2016	
Quintiles	VW	EW	VW	EW	VW	EW
Q1	-0.13	-0.24	-0.24	-0.25	-0.16	-0.27
	(-0.85)	(-1.75)	(-1.77)	(-1.57)	(-1.23)	(-2.34)
Q2	-0.07	-0.18	-0.01	-0.10	-0.11	-0.18
	(-0.68)	(-1.87)	(-0.08)	(-0.76)	(-1.18)	(-2.22)
Q3	0.10	0.14	0.11	0.23	0.12	0.14
	(1.00)	(1.36)	(0.88)	(1.69)	(1.51)	(1.67)
Q4	0.24	0.19	0.23	0.30	0.20	0.20
	(1.75)	(1.80)	(1.40)	(2.28)	(1.74)	(2.32)
Q5	0.22	0.39	0.28	0.42	0.24	0.35
	(2.11)	(2.88)	(2.41)	(2.57)	(2.76)	(3.23)
Q5 - Q1	**0.35**	**0.63**	**0.52**	**0.66**	**0.40**	**0.62**
	(1.63)	**(4.36)**	**(2.43)**	**(3.27)**	**(2.15)**	**(4.57)**

Table A3. Independent double sorts on gross profitability and competition (NYSE breakpoints)

At the end of June of each year *t*, we divide stocks into three portfolios based on NYSE breakpoints for bottom 30%, middle 40%, and top 30% of ranked values of competition proxy in year *t - 1* and independently divide stocks into five groups based on NYSE breakpoints of *GPA* in year *t - 1*. Portfolios rebalanced annually at the end of June. We reports two kinds of weighting schemes; value- (VW) and equal-weighted (EW), and the both mean excess returns and Cahart (1997) risk-adjusted alphas. Panel A, B, and C report the average returns on the periods covered with *Fit_HHI*, *Fludity*, and *Comp_HHI*, respectively. Since *Fit_HHI* and *Comp_HHI* decrease as product market competition is intensified, 'Low (High) Competition' column represents the highest (lowest) tercile based on the corresponding competition proxy. In contrast, 'Low (High) Competition' column represents the lowest (highest) tercile based on the *Fluidity*. The last column reports the difference of average excess returns and risk-adjusted returns of high and low competition tercile. Due to different coverage of competition measures, our testing periods consist of three kinds of period; July 1976 – June 2007 (sample with *Fit_HHI*), July 1998 – December 2016 (sample with *Fluidity*), and July 1977 – December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey and West (1987) adjusted t-statistics in parentheses. The important empirical results are expressed in bold letters and the symbols ***, **, and * indicates that values are significantly different from zero at the 1%, 5%, and 10% levels, respectively. At the end of June of each year *t*, we divide stocks into three portfolios based on the NYSE breakpoints for the bottom 30%, middle 40%, and top 30% of ranked values of the competition proxy in year *t* – 1 and independently divide stocks into five groups based on NYSE breakpoints of *GPA* in year *t* – 1. The portfolios are rebalanced annually at the end of June. We reports two kinds of weighting schemes, value weighted (VW) and equal weighted (EW), and both the mean excess returns and Carhart (1997) 4-factor risk-adjusted alphas. Panels A to C report the average returns on the periods covered with *Fit_HHI*, *Fluidity*, and *Comp_HHI*, respectively. Since *Fit_HHI* and *Comp_HHI* decrease as product market competition intensifies, the low (high) competition columns presents the highest (lowest) terciles based on the corresponding competition proxy. In contrast, the low (high) competition columns present the lowest (highest) terciles based on *Fluidity*. The last columns report the differences of the average excess returns and risk-adjusted returns of the high and low competition terciles. Due to differences in the coverage of the competition measures, our testing period consists of three periods: July 1976 to June 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey–West (1987) adjusted and in parentheses. The important empirical results are expressed in bold.

	Low competition				High competition				High - Low			
	GPA1	GPA3	GPA5	5 - 1	GPA1	GPA3	GPA5	5 - 1	GPA1	GPA3	GPA5	5 - 1
Panel A. Competition Proxy = Fit_HHI												
Exess returns (VW)	0.56	0.83	0.67	**0.11**	0.49	0.55	1.08	**0.59**	-0.08	-0.28	0.40	**0.48**
	(1.89)	(3.06)	(2.28)	**(0.39)**	(1.19)	(1.53)	(3.43)	**(1.95)**	(-0.22)	(-0.98)	(1.77)	**(1.37)**
Exess returns (EW)	0.40	0.90	0.89	**0.49**	0.43	0.86	1.45	**1.02**	0.03	-0.04	0.56	**0.53**
	(1.06)	(2.60)	(2.53)	**(3.06)**	(0.78)	(2.13)	(3.22)	**(3.76)**	(0.08)	(-0.18)	(2.10)	**(2.12)**
Alphas (VW)	-0.13	0.18	0.09	**0.22**	-0.33	-0.06	0.47	**0.81**	-0.20	-0.23	0.39	**0.59**
	(-0.65)	(1.10)	(0.46)	**(0.74)**	(-1.96)	(-0.31)	(3.41)	**(3.34)**	(-0.70)	(-1.04)	(1.81)	**(1.73)**
Alphas (EW)	-0.43	0.13	0.12	**0.55**	-0.18	0.21	0.89	**1.06**	0.25	0.08	0.77	**0.52**
	(-2.49)	(0.80)	(0.65)	**(3.24)**	(-0.59)	(1.28)	(3.78)	**(4.34)**	(0.93)	(0.48)	(3.37)	**(2.29)**
Panel B. Competition Proxy = Fluidity												
Exess returns (VW)	0.80	0.68	0.49	**-0.31**	0.37	0.68	0.91	**0.54**	-0.44	0.01	0.42	**0.85**

	(1.39)	(1.61)	(1.67)	**(-0.81)**	(0.66)	(1.26)	(1.92)	**(1.55)**	(-1.05)	(0.02)	(1.04)	**(2.12)**
Exess returns (EW)	0.95	1.08	1.15	**0.20**	0.59	1.09	1.43	**0.84**	-0.36	0.01	0.28	**0.64**
	(1.49)	(1.99)	(2.28)	**(0.79)**	(0.83)	(1.81)	(2.22)	**(2.86)**	(-0.77)	(0.02)	(0.59)	**(2.08)**
Alphas (VW)	0.07	0.00	0.14	**0.07**	-0.29	0.17	0.46	**0.75**	-0.35	0.17	0.32	**0.67**
	(0.21)	(0.02)	(0.88)	**(0.23)**	(-1.74)	(0.85)	(1.84)	**(2.32)**	(-0.92)	(0.62)	(1.01)	**(1.61)**
Alphas (EW)	-0.03	0.21	0.36	**0.39**	-0.29	0.29	0.64	**0.92**	-0.26	0.08	0.27	**0.53**
	(-0.13)	(1.26)	(1.92)	**(1.75)**	(-1.34)	(1.73)	(2.52)	**(3.30)**	(-0.78)	(0.40)	(0.88)	**(1.67)**
Panel C. Competition Proxy = Comp_HHI												
Exess returns (VW)	0.44	0.55	0.60	**0.16**	0.21	0.59	0.82	**0.61**	-0.23	0.03	0.22	**0.45**
	(1.76)	(2.20)	(2.42)	**(0.73)**	(0.69)	(2.17)	(3.36)	**(3.01)**	(-1.14)	(0.15)	(1.14)	**(1.72)**
Exess returns (EW)	0.39	0.90	0.97	**0.59**	0.29	0.96	1.28	**0.99**	-0.10	0.06	0.31	**0.40**
	(0.93)	(2.62)	(2.91)	**(3.43)**	(0.67)	(2.50)	(3.12)	**(4.69)**	(-0.61)	(0.33)	(1.50)	**(1.99)**
Alphas (VW)	-0.04	0.04	0.17	**0.21**	-0.37	0.12	0.52	**0.89**	-0.33	0.08	0.35	**0.68**
	(-0.27)	(0.32)	(1.31)	**(1.00)**	(-2.78)	(0.98)	(4.93)	**(4.73)**	(-1.88)	(0.41)	(2.12)	**(2.76)**
Alphas (EW)	-0.43	0.08	0.25	**0.67**	-0.40	0.26	0.71	**1.11**	0.02	0.18	0.47	**0.44**
	(-2.53)	(0.69)	(1.84)	**(4.18)**	(-1.99)	(1.93)	(3.27)	**(5.53)**	(0.15)	(1.33)	(2.49)	**(2.32)**

Table A4. Dependent double sorts on gross profitability and competition (NYSE breakpoints)

At the end of June of each year *t*, we divide stocks into three portfolios based on the NYSE breakpoints for the bottom 30%, middle 40%, and top 30% of ranked values of the competition proxy in year *t* – 1 and dependently divide stocks into five groups based on NYSE breakpoints of *GPA* in year *t* – 1. The portfolios are rebalanced annually at the end of June. We reports two kinds of weighting schemes, value weighted (VW) and equal weighted (EW), and both the mean excess returns and Carhart (1997) 4-factor risk-adjusted alphas. Panels A to C report the average returns on the periods covered with *Fit_HHI*, *Fluidity*, and *Comp_HHI*, respectively. Since *Fit_HHI* and *Comp_HHI* decrease as product market competition intensifies, the low (high) competition columns presents the highest (lowest) terciles based on the corresponding competition proxy. In contrast, the low (high) competition columns present the lowest (highest) terciles based on *Fluidity*. The last columns report the differences of the average excess returns and risk-adjusted returns of the high and low competition terciles. Due to differences in the coverage of the competition measures, our testing period consists of three periods: July 1976 to June 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey–West (1987) adjusted and in parentheses. The important empirical results are expressed in bold.

	Low competition				High competition				High - Low			
	GPA1	GPA3	GPA5	5 - 1	GPA1	GPA3	GPA5	5 - 1	GPA1	GPA3	GPA5	5 - 1
Panel A. Competition Proxy = Fit_HHI												
Exess returns (VW)	0.67	0.83	0.69	**0.02**	0.45	0.54	1.05	**0.60**	-0.22	-0.29	0.36	**0.58**
	(2.20)	(3.13)	(2.40)	**(0.09)**	(1.08)	(1.49)	(3.37)	**(1.96)**	(-0.63)	(-1.04)	(1.69)	**(1.82)**
Exess returns (EW)	0.36	0.79	0.83	**0.48**	0.42	0.83	1.43	**1.01**	0.06	0.04	0.59	**0.53**
	(0.93)	(2.27)	(2.41)	**(3.07)**	(0.75)	(2.04)	(3.19)	**(3.66)**	(0.17)	(0.17)	(2.27)	**(2.08)**
Alphas (VW)	-0.24	0.10	0.10	**0.34**	-0.37	-0.07	0.44	**0.81**	-0.14	-0.17	0.34	**0.48**
	(-1.34)	(0.69)	(0.56)	**(1.23)**	(-2.24)	(-0.41)	(3.07)	**(3.37)**	(-0.55)	(-0.81)	(1.69)	**(1.59)**
Alphas (EW)	-0.50	-0.01	0.06	**0.56**	-0.18	0.19	0.87	**1.05**	0.32	0.19	0.81	**0.49**
	(-2.92)	(-0.04)	(0.33)	**(3.47)**	(-0.60)	(1.13)	(3.63)	**(4.26)**	(1.14)	(1.11)	(3.55)	**(2.22)**
Panel B. Competition Proxy = Fluidity												
Exess returns (VW)	1.02	0.53	0.40	**-0.62**	0.39	0.62	0.72	**0.33**	-0.63	0.08	0.32	**0.95**
	(2.01)	(1.36)	(1.21)	**(-1.78)**	(0.66)	(1.24)	(1.49)	**(0.98)**	(-1.90)	(0.22)	(0.80)	**(2.38)**
Exess returns (EW)	0.94	0.97	1.19	**0.25**	0.61	0.91	1.36	**0.76**	-0.33	-0.06	0.17	**0.51**
	(1.57)	(1.85)	(2.29)	**(1.03)**	(0.82)	(1.51)	(2.14)	**(2.72)**	(-0.66)	(-0.18)	(0.37)	**(1.83)**
Alphas (VW)	0.31	0.12	-0.02	**-0.33**	-0.29	-0.01	0.30	**0.59**	-0.60	-0.12	0.32	**0.92**
	(1.41)	(0.52)	(-0.11)	**(-1.25)**	(-1.52)	(-0.03)	(1.42)	**(1.87)**	(-2.03)	(-0.45)	(1.05)	**(2.43)**
Alphas (EW)	0.01	0.14	0.41	**0.40**	-0.29	0.15	0.58	**0.87**	-0.30	0.00	0.17	**0.47**
	(0.08)	(0.83)	(1.97)	**(1.77)**	(-1.30)	(0.81)	(2.31)	**(3.32)**	(-1.00)	(0.02)	(0.53)	**(1.70)**

Panel C. Competition Proxy = Comp_HHI

Exess returns (VW)	0.52	0.53	0.63	**0.11**	0.20	0.55	0.83	**0.62**	-0.31	0.02	0.20	**0.51**
	(1.95)	(2.16)	(2.44)	**(0.50)**	(0.65)	(2.08)	(3.43)	**(3.10)**	(-1.68)	(0.10)	(1.02)	**(2.08)**
Exess returns (EW)	0.41	0.91	1.01	**0.60**	0.27	0.66	1.19	**0.93**	-0.14	-0.25	0.19	**0.32**
	(1.04)	(2.68)	(3.05)	**(4.11)**	(0.59)	(1.83)	(3.00)	**(4.47)**	(-0.74)	(-1.84)	(0.99)	**(1.92)**
Alphas (VW)	-0.11	0.00	0.18	**0.29**	-0.39	0.11	0.52	**0.90**	-0.28	0.11	0.34	**0.61**
	(-0.83)	(-0.00)	(1.32)	**(1.38)**	(-2.91)	(0.95)	(4.98)	**(4.86)**	(-1.58)	(0.62)	(1.92)	**(2.43)**
Alphas (EW)	-0.42	0.13	0.27	**0.70**	-0.41	-0.03	0.61	**1.02**	0.01	-0.16	0.34	**0.33**
	(-2.88)	(1.00)	(2.01)	**(4.81)**	(-1.90)	(-0.24)	(3.06)	**(5.34)**	(0.06)	(-1.35)	(1.99)	**(2.04)**

Table A5. Exposure to research and development (R&D) premium (NYSE breakpoints)

This table reports the summarized results of the regression coefficients as follows:

$$GPA\ premium_t = \alpha + \beta * R\&D\ premium_t + \gamma' X_t \quad where\ X = [MKTRF_t\ SMB_t\ HML_t\ UMD_t]'$$

To measure the R&D premium, we split stocks based on the NYSE breakpoints into deciles based on RD/ME and calculate monthly value-weighted decile returns from July of year *t* to June of year *t* + 1, rebalancing deciles in June of year *t* + 1. Then, using 15 (3 × 5) independently (or dependently) double-sorted portfolios based on NYSE breakpoints of competition and *GPA*, we calculate the value-weighted high-minus-low returns of the highest and lowest *GPA* quintile portfolios within each competition tercile and conduct an alpha test based on the above regression specification. To conserve space, we report only the coefficients of the R&D premium (β) and the differences of β between *GPA* spreads in the high and low competition terciles. Due to differences in the coverage of the competition measures, our testing period consists of three periods: July 1976 to une 2007 (sample with *Fit_HHI*), July 1998 to December 2016 (sample with *Fluidity*), and July 1977 to December 2016 (sample with *Comp_HHI*). All the t-statistics are Newey–West (1987) adjusted and in parentheses. The important empirical results are expressed in bold.

	Competition Level			
Competition Proxy	High	Middle	Low	High - Low
Panel A. Independent sorted portfolios				
Fit_HHI	**0.04**	0.06	-0.02	**0.06**
	(0.68)	(1.16)	(-0.23)	**(0.82)**
Fluidity	**0.21**	-0.04	0.00	**0.21**
	(3.34)	(-0.57)	(-0.04)	**(2.22)**
Comp_HHI	**0.11**	0.05	0.02	**0.09**
	(2.50)	(0.90)	(0.36)	**(2.10)**
Panel B. Dependent sorted portfolios				
Fit_HHI	**0.06**	0.04	-0.07	**0.13**
	(1.04)	(0.82)	(-0.99)	**(1.97)**
Fluidity	**0.08**	-0.05	-0.07	**0.15**
	(1.06)	(-0.63)	(-1.02)	**(1.75)**
Comp_HHI	**0.05**	0.04	0.00	**0.05**
	(1.32)	(0.72)	(0.01)	**(1.50)**