Product Market Competition and the Profitability Premium

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Abstract

This paper studies the impact of product market competition on the positive relation between profitability and average stock returns. I find that profitability positively predicts returns, only among firms in competitive industries. A long-short portfolio sorted on profitability earns an average monthly return of 1.1% in competitive industries, and only 0.14% in concentrated industries. This different performance is largely driven by firm's different exposures to investment-specific technology (IST) shocks. I develop a production-based asset pricing model with imperfect competition and growth opportunities. I show that monopolies have less incentive to invest when facing IST shocks. Thus market power lets the firms better hedge IST shocks, lowering their risk exposures than firms in competitive industries. Empirical tests on investment responses confirm the model's predictions.

Keywords: Profitability anomaly, Competition, Investment-based asset pricing.

1. Introduction

Profitable firms earn significantly higher average stock returns than unprofitable firms (Fama and French (2006), Novy-Marx (2013), and Hou et al. (2014)). The return spread is often referred to as the profitability premium. It has attracted a lot of attention among both academics and practitioners. Moreover, profitability-based factor model can help explain a large set of asset pricing anomalies (Novy-Marx (2013), Hou et al. (2014), and Fama and French (2015)). Given its extraordinary empirical explanatory power, understanding the economic source of the profitability premium is important.

In this article, I study the impact of product market competition on the profitability premium. There are a number of potential reasons why the product market competition may affect the risk profile of profitable firms. Competition drives down profit opportunities, so firms with the same current profitability, but operating in different product markets of competition, may fundamentally be different. Profits are more likely to be competed away in highly competitive markets. Thus, profitable firms' risk increases with the product market competition they face. Investors would require higher compensation for holding profitable companies' stocks in competitive industries, comparing to profitable companies' stocks in noncompetitive industries. Consistent with the intuition, I find that the profitability premium is substantially stronger among firms in competitive industries.

Specifically, Novy-Marx (2013) finds that a hedge portfolio that is long in more profitable firms and short in less profitable firms earns a monthly excess return 0.31% with t-statistic of 2.49 and a Fama French three factor model alpha 0.52 with t-statistic of 4.49. Profitability is measured by gross profitability, which is defined as total revenue minus cost of goods sold divided by total assets. Through a double sorted portfolios approach, I find that the profitability premium is small and insignificant in concentrated industries, is monotonically increasing across competition terciles, and is large and significant in competitive industries. When competition is measured using the fitted Herfindahl-Hirschman index (fitted HHI) following Hoberg and Phillips (2010), which captures the impact from both public and private firms, the high-minus-low profitability quintile portfolio mean excess returns within high, medium, and low fitted HHI tercile are 0.14%, 0.41%, and 1.10% per month, respectively, with t-statistics of 0.78, 1.48, and 3.80. The difference of the profitability premium between low and high fitted HHI tercile is also economically large and statistically significant, reaching about 1% per month with t-statistic of 3.55. The abnormal returns, measured by Fama French three factor model alpha, are also monotonically increasing across competition terciles. The difference of the risk adjusted returns between low and high fitted HHI tercile is 0.90% per month with t-statistic of 3.24.

This pattern is robust across many specifications – it holds for different profitability measures, different product market competition measures, different sorting methods, different asset pricing models, and different sample periods. Moreover, I estimate Fama and MacBeth (1973) cross sectional regressions that include a broad array of control variables and confirm the strong interaction effect between profitability and product market competition on firms' expected returns.

The average profitability premium effect still remains a puzzle in asset pricing literature. My empirical finding that the profitability premium exists primarily in competitive industries is informative about the role of product market competition in explaining this puzzle. I inspect the mechanism of the empirical finding by investigating the performance of two macro risk factors studied in Kogan and Papanikolaou (2013): total factor productivity (TFP) shock risk factor and investment-specific technology (IST) shock risk factor. The investment-specific technology shock captures the idea that technological change is embodied in new productive capital and is a source of systematic risk. Kogan and Papanikolaou (2014) show theoretically that firms deriving most of their value from growth opportunities – rather than existing assets – face a higher exposure to technological shocks embodied in new capital goods. Under certain assumptions, the marginal value of wealth is higher in states with good real investment opportunities, implying that capital-embodied technological shocks are priced and carry a negative premium (Papanikolaou (2011)). Hence, firms with more growth opportunities earn lower risk premia. In Kogan and Papanikolaou (2013), they find that profitable firms have lower exposures to IST shocks, thus are riskier and earn higher expected returns than unprofitable firms since the very profitable firms derive most of their value from the value of existing assets.

I empirically test whether firms' different exposures to IST shocks can explain the finding that the profitability premium is stronger in competitive industries. Using proxies for the IST shock based on real variables and stock returns, I follow three steps to address this question – estimate risk exposures, price of risk, and evaluate the performance of a two factor asset pricing model. I find that profitability long-short portfolio in competitive industries is more negatively exposed to IST shocks than it is in concentrated industries. It implies that the cross sectional difference in risk exposures is more pronounced among firms in competitive industries. A standard linear SDF test shows a negative price of the IST shocks. Together with the disembodied technology shocks, the two factor model can explain a sizable portion of the observed profitability premium in competitive and concentrated industries. These findings suggest that heterogeneity in firms' IST risk exposures provide a partial explanation for the different profitability premium in competitive and concentrated industries.

To assess whether the proposed explanation is quantitatively plausible, I develop a theory on competition, growth opportunities and expected returns. Unlike most investment-based asset pricing models with perfect competition assumption, I allow market power and study the implications of imperfect competition on firms' investment and expected stock returns. Firms own projects and produce output subject to aggregate and idiosyncratic productivity shocks. They face a downward-sloping demand curve in the product market and the price elasticity of demand parameter governs the degree of market power. Firms acquire new projects which arrive exogenously and make investment decisions by purchasing investment goods. The price of investment goods is subject to aggregate investment specific technology shocks. The market value of a firm is the sum of value of assets in place and value of present value of growth opportunities. Different firms have different exposures to aggregate IST shocks. Since firms do not want firm value to fluctuate over IST shocks, they want to minimize exposures to IST shocks. Because firms in competitive industries have less control over output price, their firm value is more sensitive to IST shocks. Monopoly firms have more control over output price, making them less sensitive to IST shocks. They have less incentive to invest when facing IST shocks comparing to competitive firms. Thus market power lets the firms better hedge IST shocks, lowering their risk exposures than firms in competitive industries. I calibrate the model to competitive and concentrated industries, respectively, under reasonable parameters by matching the profitability and investment moments to the data. The model is able to quantitatively match the prominent profitability premium in competitive industries and negligible return spread in concentrated industries. Further, it replicates the contrasting IST risk exposures among those portfolios.

The model has two main empirical predictions on firm's investment response to IST shocks. The first prediction is that firms with more growth opportunities, being better positioned to take advantage of positive IST shocks, should increase their investment more in response to a positive IST shock than firms with less growth opportunities. The second prediction is that firms in competitive industries should increase their investment more in response to IST shocks than firms in monopoly industries. I find strong empirical support for both predictions. Unprofitable firms invest more after IST shocks than profitable firms. Firms in competitive industries increase investment much more after IST shocks than firms in concentrated industries. This empirical fact confirms that monopolies respond less to IST shocks. Moreover, I find that unprofitable firms increase investment more after IST shocks, only for those in competitive industries. These findings further confirm the heterogeneous IST risk exposures explanation through the investment channel documented both in the empirical and theoretical part of the paper.

This paper contributes to the literature on the relation between profitability and average stock returns. Motivated by valuation theory, Fama and French (2006) employ current earnings as a measure of profitability and find that more profitable firms have higher expected returns. Novy-Marx (2013) documents the gross profitability premium. Inspired by q-theory, Hou et al. (2014) form portfolios by sorting directly on past return on equity (ROE) and find that firms with high ROE earn substantially higher returns during subsequent periods. Ball et al. (2015, 2016) document the operating profitability premium and cash profitability premium which strength the gross profitability premium. However, the understanding of the profitability premium is challenging and rare. As Novy-Marx (2013) puts, since profitable firms are less prone to distress, have longer cash flow durations, and have lower operating leverage, the leading explanations for the value premium such as q theory or duration theory have difficulty explaining the profitability premium. Wang and Yu (2013) finds that the profitability premium exists primarily among firms with high arbitrage costs or high information uncertainty. Inattention-induced underreaction can partially explanation the puzzle. Kogan and Papanikolaou (2013) propose a unified explanation for several asset pricing anomalies, including value, investment, profitability, market beta, and idiosyncratic volatility, by firm's heterogeneous exposures to IST shocks. I show that the profitability premium exists only among firms in competitive industries. This evidence suggests that competition potentially drives the positive profitability-return relation.

The evidence on the relation between industry competition and stock returns is mixed in the literature. Hou and Robinson (2006) finds that firms in more concentrated industries earn lower returns. However, recently Bustamante and Donangelo (2017) and Corhay (2017) documents that firms in more competitive industries earn lower returns. The focus of this paper is on the performance of profitability premium across different industries of competition, instead of on competition premium. It might be interesting to study how differently competition premium performs among profitable and unprofitable firms. I leave this for future research.

This paper also relates to several papers on the interaction between industry competition and other cross sectional anomalies. Giroud and Mueller (2011) find that weak governance firms have lower stock returns, but only in noncompetitive industries. The rationale is that firms in noncompetitive industries, where lack of competitive pressure fails to enforce discipline on managers, should benefit relatively more from good governance. Gu (2016) finds that R&D-intensive firms tend to be riskier and earn higher expected returns than R&D-weak firms, particularly in competitive industries. The intuition is that R&D projects are more likely to fail in the presence of more competition because rival firms could win the innovation race. I document another important role that competition plays in the riskiness among profitable and unprofitable firms.

Finally, this paper contributes to the broader strand of investment-based asset pricing literature that links firm characteristics to the cross-sectional stock returns. See, for example, Cochrane (1991), Belo and Yu (2013), Belo et al. (2014), Belo et al. (2017), Belo and Deng (2018), Li (2017), Yang (2013), Loualiche (2015), Garlappi and Song (2017), Corhay (2017), among many others.

The rest of this paper is organized as follows. Section 2 describes the data and the proxies for profitability and product market competition. Section 3 examines the relationship between competition and the profitability premium. Section 4 explores the role of investment-specific shock as an explanation. Section 5 calibrates a structural model to assess the proposed explanation quantitatively and tests model predictions in the data. Section 6 concludes.

2. Data and Measurements

I describe the data used in the empirical tests and report the characteristics of a typical firm in competitive and concentrated industries.

I take monthly stock returns from the Center for Research in Security Prices (CRSP) and annual accounting data from Compustat. To be included in the sample, a firm must have matching data in both datasets. Following Fama and French (1992), only NYSE-, Amex-, and Nasdaq-listed securities with share codes 10 and 11 are included in the sample. Thus, only firms with ordinary common equity are included (American depositary receipts, real estate investment trusts, and units of beneficial interest are excluded). Finally, the sample excludes financial firms (SICs 6000 to 6999) and regulated utilities (SICs 4900 to 4999).

To ensure that the accounting information is already publicly available, I follow Fama and French (1992) to match accounting information for all fiscal year-ends in calendar year $t-1$ with CRSP stock return data from July of year t to June of year $t+1$. Thus, a six-months gap at minimum exists between the fiscal year-end and the stock return. Since firms have different fiscal year-ends, the time gap between the accounting data and matching stock returns varies across firms.

2.1. Profitability measure

Following Novy-Marx (2013), I use gross profitability (GPA) as the main profitability measure. Other profitability measures, including return on equity (ROE) and return on assets (ROA) are also used in the robustness checks reported in the Appendix. I construct the annual GPA variable by following Novy-Marx (2013). GPA is total revenue (REVT) minus cost of goods sold (COGS) scaled by book assets (AT). This profitability measure contains expensed investments, such as research and development (R&D), advertising, or human capital development. Expensed investments directly reduce earnings without increasing book equity but are nevertheless associated with higher future profitability.

2.2. Product market competition measure

Product market competition is measured by Herfindal-Hirschman Index (HHI), a measure that is commonly used by researchers in the literature on industrial organization and policy makers in Department of Justice. Measures of HHI vary along two dimensions: sales dataset and industry classification. I adopt the fitted HHI measure at the three-digit Compustat-classified SIC code industry level suggested by Hoberg and Phillips (2010) mainly because this measure captures both public and private firms' impact on industry concentration. It combines Compustat data with Herfindahl data from the US Census Bureau which contains both public and private firms, and employee data from the Bureau of Labor Statistics (BLS) which also contains both public and private firms. More specifically, they first run Census

HHI for manufacture industry on its Compustat HHI, number of employees in BLS and number of employees in Compustat. Then they use the regression coefficients to compute fitted HHI for all industries using each industry's Compustat HHI, number of employees in BLS and number of employees in Compustat. Hoberg and Phillips (2010) describe the detailed construction of fitted HHI. The data is available annually for time periods from 1975 to 2005.

I also use the Compustat-based HHI as an alternative proxy for competition, following Hou and Robinson (2006). I construct the Compustat HHI using the firm sales data:

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

where s_{ijt} is the market share of firm i in industry j in year t. N_j is the number of firms in industry j in year t. Market share of an individual firm is calculated by using the firm's net sales (SALE) divided by the total sales value of the entire industry. Following Hou and Robinson (2006), I classify industries by 3 digit SIC codes from CRSP. SIC codes from CRSP report the time-series of industry classification codes. Compustat only reports the most recent SIC codes. All firms with non-missing sales value are included in the sample to calculate HHI. The calculation is done every year and the average value over the past two years is used as the HHI of an industry to prevent potential data errors in the analysis. The data is available for a longer period from 1963 to 2015.

3. The Role of Product Market Competition in the Profitability Premium

This section presents my main empirical findings. I explore the role of product market competition in the profitability premium through a conventional double-sorting portfolio analysis and Fama and MacBeth regressions. I use GPA to measure firm-level profitability and fitted HHI to measure product market competition in the main tests. I also use two alternative profitability measures, ROE and ROA, and one alternative competition measure Compustat HHI as robustness checks. All robustness tests are reported in the Appendix.

3.1. Portfolio analysis

In this section, I use the portfolio approach to study how the profitability premium varies with the extent of product market competition. Comparing to Fama and MacBeth regressions approach, portfolio approach weights each observation based on their market cap and does not impose specific relationship between the variables. Each June of year t, I construct fifteen portfolios by first sorting NYSE, AMEX, and NASDAQ stocks into three groups based on the tercile of the ranked values of the fitted HHI for each firm.[1] And then I sort stocks within each competition tercile into five groups based on the quintile of the ranked values of gross profitability. Monthly value-weighted excess returns on the fifteen portfolios are calculated for the period from July of year t to June of year $t+1$, and the portfolios are rebalanced in June of each year.

Table 1 reports the monthly profitability quintile portfolios, and the high-minus-low

[1] An alternative way of sorting stocks into HHI terciles would be to use industry- rather than firm-level HHI cutoffs. My results are quantitatively similar.

portfolio value-weighted excess returns within each competition tercile and the corresponding t-statistics. Besides examining the raw excess portfolio returns, I also investigate whether the spreads can be explained by the traditional Fama and French (1993) three-factor model. If this classic model can capture the cross-sectional variation in stock returns, the intercept from the following regressions should be statistically indistinguishable from zero:

$$R^{ex}_{i,t} = \alpha + b_i MKT_t + s_i SMB_t + h_i HML_t + \epsilon_{i,t} \tag{2}$$

where $R^{ex}_{i,t}$ is the return of portfolio i in excess of the risk-free rate in month t, MKT_t is the value-weighted market return minus the risk-free rate in month t, SMB_t and HML_t are the month t size and book-to-market factor. Table 1 also reports the intercepts, factor loadings and their t-statistics from the above regression.

[Table 1 here]

Based on Table 1, I find that the profitability premium is monotonically increasing with industry competition. There is an insignificant (t-statistic = 0.78) monthly profitability premium 0.14% among firms in most concentrated industries (highest fitted HHI tercile). In the middle fitted HHI tercile, the profitability premium is 0.41% per month with t-statistic of 1.48. Most of the profitability premium is among firms in most competitive industries (lowest fitted HHI tercile) with a monthly return spread 1.10% and t-statistic of 3.80. The last column of Table 1 reports the difference of the profitability premium across industries of high and low competition. I'm more interested in this difference, instead of how significant profitability premium itself is in each competition tercile. The difference is about 1% per month with t-statistic of 3.55. The magnitude is economically large: the profitability premium is more than 1% per month higher among firms in competitive industries than that among firms in concentrated industries. The risk-adjusted alpha is generally more significant and monotonically increasing with industry competition. This is partly because the high-minus-low profitability portfolios have a negative loading on the market and the HML factor. In untabulated analysis, I find that the difference-on-differences are still significant even after I adjust the raw excess returns with CAPM or Fama and French five factor model.

One concern about the previous portfolio approach is that the profitability premium is also larger among firms in competitive industries. Thus, to alleviate this concern, I also report the results based on independently sorted portfolios in Table 2. The pattern remains largely the same. The mean profitability premium increases from 0.14% in the most concentrated industries to 0.97% in the most competitive industries. The difference between these two groups is 0.82% per month with t-statistic of 3.10. In untabulated analysis, I also form portfolios by sorting profitability first and then sorting on industry competition. Moreover, I also sort portfolios with different number of bins, such as three competition and three profitability portfolios, three competition and ten profitability portfolios, and five competition and five profitability portfolios. The results, omitted by brevity, are quantitatively similar. In addition, I use Fama and MacBeth regressions to further address this concern in the next subsection.

[Table 2 here]

Figure 1 provides a visual description of Table 1, which plots the average excess return for each competition and profitability sorted portfolio.

[Figure 1 here]

In sum, the profitability premium exists primarily in competitive industries. This finding suggests that the positive profitability-return relation identified in prior studies is an average effect of firms from industries with different degrees of competition.

3.2. Fama and MacBeth regressions

The simple double-sorting approach in the previous subsection delivers the main empirical finding that profitability predicts returns, only in competitive industries. However, this finding could possibly be driven by other forces not being controlled in the portfolio analysis. Besides, sorting on three or more variables is impractical. Thus, to investigate other possible mechanisms, I perform Fama and MacBeth (1973) cross sectional regressions, which allow me to conveniently control for additional variables.

The multivariate regressions are specified as follows:

$$R_{i,j,t+1} = \beta_0 + \beta_1 GPA_{i,j,t} + \beta_2 X_{i,j,t} + \beta_3 GPA_{i,j,t} * X_{i,j,t} + Controls_{i,j,t} + \epsilon_{i,j,t+1} \quad (3)$$

where $R_{i,j,t+1}$ is the month $t+1$ raw returns on stock i in industry j, $GPA_{i,j,t}$ is the gross profitability of firm i in industry j at month t, and $X_{i,j,t}$ is the proxy for industry competition for firm i in industry j at month t. I use fitted HHI as the first proxy for $X_{i,j,t}$, higher the proxy, less competitive the industry is. To mitigate the measurement problems of HHI which are sometimes an issue with the HHI, I identify competitive industries by using dummy variables as the second proxy. I define the dummy variable *Comp*, which equals one if the fitted HHI is in the lowest tercile of the yearly sample distribution, and equals zero otherwise. This dummy variable also allows for an intuitive economic interpretation of coefficient estimates. $Controls_{i,j,t}$ include book-to-market ($log(B/M)$), size ($log(ME)$), and past performance measured at horizons of one month ($r_{1,0}$) and twelve to two months

($r_{12,2}$). [2] Independent variables are trimmed at the 1% and 99% levels. The t-statistics are calculated using Newey and West (1987) standard errors.

The coefficient of interest is the coefficient on the interaction term of profitability and competition, i.e. Interaction in Table 3. Table 3 reports all parameter estimates. For the fitted HHI as the first proxy, the coefficient on the interaction term is significantly negative, implying that after controlling other prominent return predictors in the cross section, the predicting power of gross profitability is significantly decreasing as industry competition decreases. Similarly, in the dummy variable specification, the coefficient on the interaction term is significantly positive, suggesting that profitability predicts returns, more significantly in competitive industries than it is in concentrated industries.

[Table 3 here]

In sum, both portfolio approach and regression tests show that the profitability premium is much stronger among firms in competitive industries. Moreover, given that profitable firms on average earn much more positive and significant abnormal returns than unprofitable firms, profitability affects firms' risk and return profiles. However, these effects can be very different for firms with the same level of profitability, but operating in different industries of competition. In fact, the profitability premium exists primarily in competitive industries. Therefore, competition plays a prominent role in the profitability premium.

[2] Book-to-market is book equity at the end of fiscal year $t-1$ scaled by market equity at the end of December of year $t-1$. Book equity is shareholder equity, plus deferred taxes, minus preferred stock, when available. For the components of shareholder equity, I employ tiered definitions largely consistent with Fama and French (1993). Stockholder equity is as given in Compustat (SEQ) if available, or else common equity plus the carrying value of preferred stock (CEQ+PSTX) if available, or else total assets minus total liabilities (AT-LT). Deferred taxes is deferred taxes and investment tax credits (TXDB and/or ITCB). Preferred stock is redemption value (PSTKR) if available, or else liquidating value (PSTKRL) if available, or else carrying value (PSTK).

4. Inspecting the Mechanism

This section explores the connection between industry competition, firm profitability and investment-specific technology shocks following Kogan and Papanikolaou (2013). And I find that firms' heterogeneous IST shock exposures largely account for the above empirical finding.

Kogan and Papanikolaou (2013) is the only published paper, to the best of my knowledge, attempting to explain the profitability premium. They start with the standard market firm value (V) decomposition into assets in place (VAP) and growth opportunities (PVGO). These two components have different exposures to aggregate shocks. VAP only depends on aggregate productivity shock and PVGO depends both on aggregate productivity shock and investment-specific shock. IST shock captures the idea that technological change is embodied in new productive capital and is a source of systematic risk. It features a negative price of risk (documented in previous literature and also confirmed in Section 4.3). Since it reduces the investment costs for firms that have a larger share of PVGO/V, a positive IST shock has a larger positive impact on the market value of such firms. Thus, firms with less exposure to IST shock are riskier, thus have higher expected returns. Since profitable firms derive most of their market firm value from existing projects (VAP), they have smaller fraction of PVGO/V than unprofitable firms and less exposure to IST shock. They are riskier and have higher expected returns. In their paper, they show that a few cross sectional anomalies, including value, investment, profitability, market beta, and idiosyncratic volatility are largely driven by differences in exposures of firms to the IST risk factor. Through a structural model, they further show that these firm characteristics are correlated with the ratio of growth opportunities to firm value, which affects firms' exposures to IST shocks and risk premia.

In order to study the explaining power of two macro risk factors proposed in previous literature in explaining the new empirical finding here, I follow three steps to investigate why profitability portfolio is riskier in competitive industries:

- IST-risk exposures
- Price of risk
- Asset pricing test of a two factor model

4.1. IST-risk exposures

I examine the role played by the IST risk factor. In particular, I regress the profitability portfolio returns across different industries of competition directly on the IST shocks. Following Papanikolaou (2011), I consider two measures of IST shock during the analysis. The first measure is constructed from the change $\triangle z_t^I$ in the detrended quality-adjusted relative price of new capital goods. The second measure relies on the relative stock returns of investment and consumption producers (IMC). Papanikolaou (2011) and Kogan and Papanikolaou (2013) show that IMC portfolio returns provide a useful empirical proxy for IST shocks.

The time series regressions are conducted as follows. I use annual portfolio returns to estimate IMC beta.

$$R_t = \alpha + \beta^{IMC} R_t^{IMC} + \epsilon_t, t = 1, 2..., T \tag{4}$$

Table 4 reports the IMC beta estimates and the corresponding t-statistics for the conditionally three by five sorted competition and profitability portfolios. The last column reports the difference in IST beta between profitability portfolio in competitive and concentrated industries. I include two measures of product market competition (fitted HHI, Compustat HHI) and three measures of profitability (GPA, ROE, and ROA). To save space, I only report the first, third, and fifth bins for the profitability quintile portfolios. From Table 4, I first find consistent results with Kogan and Papanikolaou (2013) that profitable firms are significantly less exposed to IST shocks (smallerβ^{IMC}) than unprofitable firms, for all profitability measures. Because of the negative price of IST risk, this is the main driver for the profitability premium on average. Since IMC beta is also a proxy for PVGO/V, this implies that profitable firms tend to have smaller share of growth opportunities, since the value of existing assets account for a larger share of firm value. Second, this different IST-risk exposures varies across product market competition. For all four specifications, profitability portfolio in competitive industries are more exposed IST shocks in absolute term than it is in concentrated industries. Three out of four are statistically significant. For example, in ROA and fitted HHI specification, profitability long-short portfolio in competitive industries has a IST shock beta of -1.06, comparing to a IST shock beta of -0.40 for the profitability portfolio in concentrated industries. The pattern is monotone across competition terciles. The difference in IMC beta between competitive and concentrated industries is -0.49 with t-statistic of -2.21. In GPA and Compustat HHI specification, profitability portfolio in competitive industries has a significant IST shock beta of -0.88, comparing to an insignificant IST beta of -0.23 for the profitability portfolio in concentrated industries. The difference is -0.64 with t-statistic of -3.09.

[Table 4 here]

In sum, firms with similar profitability, but in different industries of competition, have quite different exposures to certain systematic risk factor, here the IST risk factor. Profitability portfolio in competitive industries are more exposed to IST shocks in absolute term than in monopoly industries. This heterogeneous IST-risk exposure plays a key role in the performance of the profitability premium in competitive and concentrated industries. Next, I estimate the market price of the IST and the total productivity shocks. Moreover, I evaluate the extent to which the differences in IST risk exposures contribute to the differences in risk premium.

4.2. Linear SDF test

One key assumption explaining my empirical finding is a negative price of the IST risk factor. It is the case documented in Papanikolaou (2011), Kogan and Papanikolaou (2014), Kogan and Papanikolaou (2013) and among others. And this subsection formally estimates the market prices of the risk factors.

In particular, I specify the stochastic discount factor (SDF) as

$$m = a - \gamma_x \Delta x - \gamma_z \Delta z \tag{5}$$

where Δx refers to disembodied technology shocks and Δz refers to investment-specific technical change (IST). I normalize Δx and Δz to unit standard deviation so that γ_x and γ_z can be interpreted as the Sharpe ratio of a test asset perfectly correlated with Δx and Δz, respectively. I estimate the parameters using the generalized method of moments (GMM). The moment condition is

$$E[R_i^e] = -cov(m, R_i^e) \tag{6}$$

where R_i^e denotes the excess return of portfolio i over the risk-free rate. As test assets, I use five profitability portfolios in both concentrated and competitive industries tercile, resulting in ten test portfolios. I also use only five profitability portfolios in competitive industries tercile as test portfolios given the empirical fact documented above. I report first-stage GMM estimates using the identity matrix to weight moment conditions, and adjust the standard errors using Newey-West procedure with a maximum of three lags. As a measure of fit, I report the mean squared errors (MSE) and the mean absolute pricing error (MAPE) from the Euler equations. In particular, I use two-factor specifications with the market portfolio and the IMC portfolio for the SDF. I use annual portfolio returns.

Results are reported in Table 5. In both specifications of test assets, the estimated price of risk for the market factor are significantly positive. The point estimates of the market price of IST shocks are negative and statistically significant, implying a negative relation between average returns and the IST shock exposures. In addition, the pricing error are substantially reduced by the addition of the IST shock to the SDF. The CAPM results in a mean squared pricing errors of 4.01% when using five test portfolios, while the combination of market portfolio with the IMC portfolio returns produce MSE values of 1.97%.

[Table 5 here]

This subsection confirms that cross sectional differences in IST risk exposures among the test portfolios account for a sizable portion of the differences in their average returns. Next, I develop an investment-based asset pricing model with imperfect competition to evaluate if the model can quantitatively replicate the empirical findings.

5. Model

In this section I solve and calibrate a continuous-time quantitative model on competition, growth opportunities, and IST shocks to explain both price (profitability premium) and quantities (risk exposures) facts from the empirical work. I also test the new empirical predictions out of the model.

5.1. Production economy

There are two sectors in the economy, one sector producing consumption goods and the other sector producing investment goods. Both sectors feature a continuum of measure one of infinitely lived competitive firms financed only by equity. I focus on the sector producing consumption goods.

5.1.1. Assets in place

Each consumption firm $f \in [0,1]$ owns a finite number of individual projects. The set of projects owned by firm f at time t is J_{ft}. Output produced by project j is

$$y_{fjt} = u_{jt} x_t K_j^{\alpha} \tag{7}$$

where K_j is physical capital chosen irreversibly at the project j's inception date, u_{jt} is the project-specific component of productivity. Its logarithm follows an OU process and x_t is the disembodied productivity shock affecting output of all existing projects.

$$dlogu_{jt} = -\theta_u logu_{jt} dt + \sigma_u dB_{jt} \tag{8}$$

$$dx_t = \mu_x x_t dt + \sigma_x x_t dB_{xt} \tag{9}$$

where dB_{jt} and dB_{xt} are independent standard Brownian motions.

The production function features decreasing returns to scale at the project level, $\alpha \in (0,1)$. Projects expire independently at rate δ.

The demand curve for the firm's output of each project is

$$y_{fjt} = x_t(p^y_{fjt})^{-\nu} \tag{10}$$

where p^y_{fjt} is the product price of output and ν is price elasticity of demand. This elasticity of demand parameter captures degree of industry competition. When ν is large, it implies tougher competition, a single firm has less control on the output price and faces a more elastic demand curve. When ν goes to infinity, demand curve is horizontal and that proxies for perfect competition. When ν is finite, firm has some control on the output price and thus some degree of market power in the product market.

5.1.2. Investment opportunities

Consumption firms acquire new projects according to a Poisson count process N_{ft} with a firm-specific arrival rate λ_{ft}. The firm-specific arrival rate of new projects has two components, $\lambda_{ft} = \lambda_f \tilde{\lambda_{ft}}$. The first component, λ_f, is constant over time and determines the size of the firm in the long run. The second component, $\tilde{\lambda_{ft}}$, captures the current state of the firm in terms of investment opportunities. I assume that $\tilde{\lambda_{ft}}$ follows a two-state, continuous-time Markov process $\tilde{\lambda_{ft}} \in [\lambda_L, \lambda_H]$ with $\lambda_H > \lambda_L$ and $\mu_H dt$ and $\mu_L dt$ denote the instantaneous probability of entering each state, respectively. Thus, at any point in time, a firm can be either in the high growth $(\lambda_f \lambda_H)$ state or the low growth state $(\lambda_f \lambda_L)$. The transition probability matrix between time t and $t + dt$ is given by

$$P = \begin{pmatrix} 1 - \mu_L dt & \mu_L dt \\ \mu_H dt & 1 - \mu_H dt \end{pmatrix} \tag{11}$$

Without loss of generality, I impose the normalization $E[\tilde{\lambda_{ft}}] = 1$. This imposes a restriction as

$$\frac{\mu_H}{\mu_H + \mu_L}\lambda_H + \frac{\mu_L}{\mu_H + \mu_L}\lambda_L = 1 \tag{12}$$

At each period of time, firm either gets one project with probability $\lambda_{ft}dt$ or not. When faced with a new project, firm chooses optimal investment level K_j and buy capital goods at a price p^I based on a tradeoff between the market value of a new project and the cost of physical capital. At the time of investment, the project-specific component of productivity is at its long-run average value, $u_{jt} = 1$. The price of investment goods is equal to $p^I = \frac{x_t}{z_t}$, where

$$dz_t = \mu_z z_t dt + \sigma_z z_t dB_{zt} \tag{13}$$

and $dB_{zt}dB_{xt} = 0$.

The z shock is the embodied, investment-specific shock. A positive change in z reduces the cost of new capital goods and thus leads to an improvement in investment opportunities.

5.2. Valuation

The stochastic discount factor π_t is exogenously given as

$$\frac{d\pi_t}{\pi_t} = -r_f dt - \gamma_x dB_{xt} - \gamma_z dB_{zt} \tag{14}$$

where the two aggregate shocks x_t and z_t have constant prices of risk, γ_x and γ_z, respectively. The risk-free interest rate r_f is also constant.

The market value for a firm is the sum of the value of assets in place VAP_{ft} and the value of present value of growth opportunities $PVGO_{ft}$.

The present value of cash flows of project j still alive at t equals to

$$p(u_{jt}, x_t, K_j) = E_t[\int_t^{\infty} e^{-\delta(s-t)} \frac{\pi_s}{\pi_t} (p^y_{fjs} u_{js} x_s K_j^{\alpha}) ds] \tag{15}$$

And value of assets in place is the sum of all the projects each firm owns

$$VAP_{ft} = \sum_{j \in J_{ft}} p(u_{jt}, x_t, K_j) = x_t \sum_{j \in J_{ft}} A(u_{jt}) K_j^{\alpha(1-\frac{1}{\nu})} \tag{16}$$

where

$$A(u_{jt}) \equiv \int_t^{\infty} \{ e^{(-\delta - r_f + \mu_x - \gamma_x \sigma_x)(s-t) + (1-\frac{1}{\nu})[log u_{jt} e^{-\theta_u (s-t)} + \frac{1}{2} \frac{\sigma_u^2}{2\theta_u} (1 - e^{-2\theta_u (s-t)})]} \} ds \tag{17}$$

The PVGO equals to the expected discounted net present value of future investments

$$PVGO_{ft} = E_t[\int_t^{\infty} \frac{\pi_s}{\pi_t} \lambda_{fs} max(p(1, x_s, K_j) - p^I_s K_j) ds] = x_t z_t^{\frac{\alpha(1-\frac{1}{\nu})}{1-\alpha(1-\frac{1}{\nu})}} G(\lambda_{ft}) \tag{18}$$

where

$$G(\lambda_{ft}) = \begin{cases} \lambda_f (\alpha(1-\frac{1}{\nu})^{-1} - 1) (\frac{\alpha(1-\frac{1}{\nu})}{r_f + \gamma_x \sigma_x + \delta - \mu_x})^{\frac{1}{1-\alpha(1-\frac{1}{\nu})}} [\frac{1}{\rho} + \frac{1}{\rho + \mu_L + \mu_H} (\lambda_H - \lambda_L) \frac{\mu_L}{\mu_L + \mu_H}], \tilde{\lambda_{ft}} = \lambda_H \\ \lambda_f (\alpha(1-\frac{1}{\nu})^{-1} - 1) (\frac{\alpha(1-\frac{1}{\nu})}{r_f + \gamma_x \sigma_x + \delta - \mu_x})^{\frac{1}{1-\alpha(1-\frac{1}{\nu})}} [\frac{1}{\rho} - \frac{1}{\rho + \mu_L + \mu_H} (\lambda_H - \lambda_L) \frac{\mu_H}{\mu_L + \mu_H}], \tilde{\lambda_{ft}} = \lambda_L \end{cases} \tag{19}$$

where $\rho = r_f + \gamma_x \sigma_x - \mu_x - \frac{\alpha(1-\frac{1}{\nu})}{1-\alpha(1-\frac{1}{\nu})} (\mu_z - \frac{1}{2}\sigma_z^2 - \gamma_z \sigma_z) - \frac{1}{2} (\frac{\alpha(1-\frac{1}{\nu})}{1-\alpha(1-\frac{1}{\nu})})^2 \sigma_z^2$ is a constant.

The optimal investment level can be solved as

$$K_j^* = z_t^{\frac{1}{1-\alpha(1-\frac{1}{\nu})}} \left(\frac{\alpha(1-\frac{1}{\nu})}{r_f + \gamma_x \sigma_x + \delta - \mu_x} \right)^{\frac{1}{1-\alpha(1-\frac{1}{\nu})}} \tag{20}$$

The optimal investment only depends on the IST shock. So at any point of time, for firms which receive a project, the investment level is the same for all firms in the same industry. The amount of investment also depends on the price elasticity of demand ν. Given the analytical form of investment, an important prediction of the model is that firms in more competitive industries (higher ν) respond more positively to IST shocks through investment than firms in less competitive industries. I will test this prediction in Section 5.5.

The total value of the firm is

$$V_{ft} = x_t \sum_{j \in J_{ft}} A(u_{jt}) K_j^{\alpha(1-\frac{1}{\nu})} + x_t z_t^{\frac{\alpha(1-\frac{1}{\nu})}{1-\alpha(1-\frac{1}{\nu})}} G(\lambda_{ft}) \tag{21}$$

5.3. Risk and risk premia

Next, I illustrate the mechanism generating cross sectional dispersion in risk exposures and risk premia in the model. All firms have the same sensitivity to the disembodied productivity shock $\beta_{ft}^x = 1$. In contrast, the firm's stock return sensitivity to the IST shock z is a function of the ratio of firm growth opportunities to firm value, PVGO/V and also depends on price elasticity of demand

$$\beta_{ft}^z = \frac{\partial ln V_{ft}}{\partial ln z_t} = \frac{\alpha(1-\frac{1}{\nu})}{1-\alpha(1-\frac{1}{\nu})} \frac{PVGO_{ft}}{V_{ft}} \tag{22}$$

Therefore, firms with more growth opportunities or firms in more competitive industries have more exposures to IST shocks as I show quantitatively later. This implication is also confirmed empirically in the IST risk exposures section above.

The risk premium on assets in place is

$$\frac{1}{dt}E_t[R_{ft}^{VAP}] - r_f = -Cov(\frac{d\pi_t}{\pi_t}, \frac{dVAP_{ft}}{VAP_{ft}}) = \gamma_x \sigma_x \tag{23}$$

The risk premium on growth options is

$$\frac{1}{dt}E_t[R_{ft}^{PVGO}] - r_f = -Cov(\frac{d\pi_t}{\pi_t}, \frac{dPVGO_{ft}}{PVGO_{ft}}) = \gamma_x \sigma_x + \frac{\alpha(1-\frac{1}{\nu})}{1-\alpha(1-\frac{1}{\nu})}\gamma_z \sigma_z \tag{24}$$

Thus, the firm's risk premium is

$$\frac{1}{dt}E_t[R_{ft}] - r_f = \gamma_x \sigma_x + \frac{\alpha(1-\frac{1}{\nu})}{1-\alpha(1-\frac{1}{\nu})}\gamma_z \sigma_z \frac{PVGO_{ft}}{V_{ft}} \tag{25}$$

Whether a firm's expected return is increasing or decreasing in the share of growth opportunities in firm value depends on the sign of the risk premium γ_z of the IST shock. A negative sign for γ_z is consistent with the empirical evidence in Section 4.

Risk premium differs across firms by the ratio of growth opportunities to firm value as well as the industry specific competition level.

The ratio of growth opportunities to firm value PVGO/V, which is a key variable summarizing firm heterogeneity in IST risk exposures, and thus risk premium, evolves endogenously as a function of the likelihood of acquiring new projects λ_{ft}, the history of project arrival and expiration, and the level of idiosyncratic productivity u_{jt}. So firms with more growth options are less risky and have lower risk premium since growth options act as a hedge for shocks to real investment opportunities.

Firms in monopoly industries have more control over output price, lowering their exposures to IST shocks. Their firm values are less sensitive to IST shocks. Therefore the risk premium is lower. In contrast, because competitive firms have less control over output price, their firm values are more sensitive to IST shocks.

5.4. Calibration

Here, I explore the ability of the model to quantitatively replicate the profitability premium in competitive and concentrated industries as well as heterogeneous IST risk exposures.

5.4.1. Parameters and calibration

The model features 18 parameters. Mostly I follow Kogan and Papanikolaou (2013). Table 6 summarizes the parameter choices. In particular, there are four groups of parameters.

[Table 6 here]

For the technology group parameters, I choose the parameters governing the dynamics of the two aggregate shocks ($\mu_x = 0.25\%$, $\sigma_x = 8.1\%$) and ($\mu_z = 0.1\%$, $\sigma_x = 3.9\%$) to match the first two moments of the aggregate dividend growth and investment growth. I select the parameters governing project cash flows ($\theta_u = 0.03$, $\sigma_u = 0.6$) to jointly match the serial autocorrelation and the cross-sectional distribution of firm-specific profitability and investment.

For the production group parameters, I calibrate the returns-to-scale parameter $\alpha = 0.9$. I choose the profit margin of investment firms $\phi = 0.075$ to match the relative size of the consumption and investment sector in the data. I set the project expiration rate $\delta = 10\%$.

The only parameter that is different across industries is the price elasticity of demand ν. I set $\nu = 18$ for highly competitive industries, $\nu = 5$ for medium competitive industries and $\nu = 1.2$ for monopoly industries to match the first and second moments of investment rate and profitability in competitive and concentrated industries. I choose three parameterization exactly to match my empirical procedures.

For the investment group parameters, I calibrate the dynamics of the stochastic component of the firm-specific arrival rate ($\mu_H = 0.01$, $\mu_L = 0.1$, and $\lambda_H = 10$) to match the time-series autocorrelation and cross-sectional dispersion of the firm-specific investment rates. I model the distribution of mean project arrival rates across firms as a uniform distribution $\lambda_f \sim U[\underline{\lambda}, \bar{\lambda}]$. I calibrate the parameters of the distribution of λ_f ($\underline{\lambda} = 5, \bar{\lambda} = 25$) to match the average investment rate and the cross-sectional distribution of the investment rate and profitability.

For the SDF group parameters, I set the interest rate to $r = 3\%$, which is close to the historical average risk-free rate. I pick the price of risk of the IST shock $b_z = -0.7$, which is similar to the price of risk estimates in Section 4.3. I choose the price of risk of the TFP shock $b_x = 2$ to match the historical equity premium.

I simulate the model at weekly frequency ($dt = 1/52$) and time-aggregate the data to form annual observations. I simulate 100 samples of 2000 firms over a period of 100 years. I drop the first half of each simulated sample to eliminate the dependence on initial values.

In Table 7, I compare the estimated moments in the data to the median moment estimates in simulated data. In most cases, the median moment estimate of the model is close to the empirical estimate. One exception is that the model generates a higher median estimate of profitability in concentrated industries. I believe it can be matched with more detailed calibration. And I'm also going to expand the number of moments in the cross section to be matched such as Tobin's Q etc. Note that in the data, firms in competitive industries have lower level, much more volatile and less persistent profitability than firms in noncompetitive industries. Moreover, firms in competitive industries invest more than firms in concentrated industries. Also these investments are more volatile and less persistent. These align well with intuition.

[Table 7 here]

5.4.2. Results in simulated data

I focus on whether the model can replicate the profitability premium across industries of different competition and their different IST risk exposures. Focusing on the ability of the model to replicate these empirical patterns using a common set of structural parameters allows me to test whether dispersion in IST risk exposures provides a quantitatively plausible explanation for the empirical findings.

I repeat the portfolio analysis procedures in Section 3.1 in simulated data from the model. In the model, the gross profits over assets measure is defined as $\frac{E_{ft}}{B_{ft}} = \frac{x_t \sum_{j \in J_{ft}} (u_{jt} K_j^{\alpha})^{1-\frac{1}{\nu}}}{p_t^I \sum_{j \in J_{ft}} K_j}$. I summarize the results in Table 8. The model generates much stronger profitability premium in competitive industries. The differences in average returns between the top and bottom decile portfolios is 0.57% per month. The profitability premium is decreasing as industry competition decreases. And there is no profitability premium in concentrated industries in simulated data. In addition, the model generates the IST risk exposures pattern as in the data. The profitability long-short portfolio in competitive industries has a more negative exposure to IST shock than it is in concentrated industries. Since IST risk features a negative market price of risk, it makes the profitability strategy riskier, thus earning higher premium in competitive industries.

[Table 8 here]

5.5. *Model predictions*

In this subsection, I explore the empirical predictions of the model.

The main mechanism of the model is that firms must invest to realize their growth opportunities. There are two important predictions on firms' investment responses to IST shocks.

1. Firms with more valuable growth opportunities, being better positioned to take advantage of positive IST shocks, should increase their investment more in response to a positive IST shock than firms with less valuable growth opportunities.

2. Firms in competitive industries increase investment more in response to positive IST shocks.

In order to empirically test these predictions, I estimate the following specification,

$$i_{ft} = b_1 \triangle z_{t-1} + \sum_{d=2}^{5} b_d D(G_{ft-1})_d \triangle z_{t-1} + \rho i_{ft-1} + \gamma X_{ft-1} + u_{ft} \tag{26}$$

where i_{ft} is the firm's investment rate; $\triangle z \in \{\triangle z^I, R^{imc}\}$ is the measure of the IST shock. The dummy variable $D(G_{ft-1})_d$ takes the value of one if the firm's gross profitability belongs to the quintile d in year $t-1$. I standardize all right-hand side variables to zero mean and unit standard deviation. I cluster standard errors by firm and year. The vector X includes the dummy variables $D(G_f)$ and firm fixed effects. The coefficient of interest is b_5, which captures the differential response of investment to the IST shock across firms in the top and bottom quintiles.

First, in Table 9, I find that on average, unprofitable firms exhibit investment behavior that is more sensitive to the two proxies for the IST shock, compared with most profitable firms. The economic magnitude is substantial. A single-standard-deviation positive IMC return shock leads to an increase in the investment to capital ratio of unprofitable firms by 1.05%, relative to profitable firms. For comparison, the median investment rate in the sample is 13%. This dispersion in investment responses suggests that unprofitable firms are positioned with more investment opportunities than profitable firms. Besides, I find that firms in competitive industries are richer or more sensitive in investment opportunities than firms in concentrated industries and the difference is statistically significant. A one-standard-deviation positive IMC return shock is associated with an increase in investment to capital ratio of firms in competitive industries by 2.52% relative to firms in concentrated industries, confirming the model's both predictions.

[Table 9 here]

Then, I use profitability quintile portfolios in low and high fitted HHI terciles to test equation (26) respectively. The goal is to test whether (un)profitable firms respond differently to IST shocks in competitive industries and concentrated industries. Table 10 shows the coefficient estimates of bs and the corresponding t-statistics. Among competitive industries, a one-standard-deviation IST shock leads to an increase in investment to capital ratio of unprofitable firms by 4.97%. But there's only 0.73% increase for unprofitable firms in concentrated industries, suggesting that investment opportunities are much more valuable in competitive industries. More importantly, in competitive industries, the differential response of investment across unprofitable and profitable firms is as large as 3.33% and statistically significant. There is no such pattern among concentrated industries. Thus, I confirm in the data the predictions of the model and show that profitability and competition are correlated with growth opportunities. Firms with similar profitability, but operating in different industries of competition, are very different in their investment behaviors as well.

[Table 10 here]

6. Conclusion

The profitability premium has attracted a lot of attention among both academics and practitioners. This paper approaches this asset pricing puzzle by studying the impact of product market competition on the profitability premium. Empirically, I find that profitability predicts returns, only among firms in competitive industries. Intuitively, profits are more likely to be competed away in highly competitive markets. Therefore, profitable firms' risk increases with their product market competition. When exploring the mechanism, I find that profitability long-short portfolio in competitive industries has more negative exposures to the investment-specific technology (IST) shocks than it is in concentrated industries, making this strategy riskier, thus earning higher risk premium. And this different exposures to IST shocks can account for a sizable portion of the profitability premium across competitive and concentrated industries.

Theoretically, I build an investment-based asset pricing model featuring imperfect competition, growth opportunities and expected returns to quantitatively replicate the empirical findings. I show that market power lets the firms better hedge aggregate shocks, thus lowering their risk exposures than firms in competitive industries. Model's empirical predictions on investment are supported in the data. It also implies that profitability and competition are correlated with firms' growth opportunities. Overall, these findings suggest that product market competition has a significant impact on profitable firms' risk and return and potentially drives the profitability premium.

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Table 1: Portfolios conditionally sorted by competition and gross profitability

This table reports the mean value-weighted returns and Fama-French three-factor αs and factor loadings on portfolios conditionally sorted on product market competition and gross profitability. Product market competition is measured by the Herfindahl-Hirschman Index (HHI) in Hoberg and Phillips (2010). Gross profitability is defined as revenue minus cost of goods sold scaled by total assets [(REVT-COGS)/AT]. In June of each year t, NYSE, Amex, and Nasdaq stocks are first sorted into three groups based on the tercile of the ranked values of HHI in year $t-1$, and then sorting stocks within each tercile into five groups based on the quintile of the ranked values of gross profitability in year $t-1$. Monthly returns on the resulting fifteen portfolios are then calculated from July of year t to June of year $t+1$. Monthly portfolio abnormal returns and factor loadings are computed by running time series regression of portfolio excess returns on Fama-French three-factor model. The sample period is from July 1976 to June 2007. The excess returns and αs are in percentages, and the t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error with three lags.

	HHI_L				HHI_M				HHI_H				$HHI_L - HHI_H$
	$Prof_L$	$Prof_3$	$Prof_H$	H-L	$Prof_L$	$Prof_3$	$Prof_H$	H-L	$Prof_L$	$Prof_3$	$Prof_H$	H-L	H-L
R^{ex}	0.05	0.64	1.15	1.10	0.25	0.67	0.66	0.41	0.56	0.58	0.70	0.14	0.96
	0.13	1.94	3.25	3.80	0.63	2.44	2.45	1.48	2.29	2.42	2.77	0.78	3.55
α	-0.72	-0.04	0.71	1.43	-0.46	0.07	0.38	0.84	-0.35	-0.20	0.19	0.53	0.90
	-3.29	-0.25	4.00	4.88	-2.56	0.56	2.53	3.58	-2.72	-1.64	1.23	2.86	3.24
b	1.26	1.14	0.99	-0.27	1.17	1.04	0.84	-0.32	1.10	1.02	0.89	-0.21	-0.06
	24.80	28.32	22.82	-3.60	24.98	27.65	22.12	-5.20	30.90	29.27	19.06	-4.36	-0.77
s	0.44	0.21	0.35	-0.09	0.60	0.05	-0.18	-0.78	0.05	-0.03	-0.10	-0.16	0.07
	5.59	2.68	3.83	-0.67	9.01	0.90	-3.02	-8.60	0.92	-0.47	-1.62	-2.33	0.48
h	-0.28	-0.16	-0.63	-0.35	-0.40	-0.11	-0.45	-0.05	0.56	0.39	0.00	-0.55	0.20
	-2.18	-1.88	-5.80	-1.98	-5.47	-2.02	-6.50	-0.50	8.45	5.34	0.07	-6.40	1.26

Table 2: Portfolios independently sorted by competition and gross profitability

This table reports the mean value-weighted returns and Fama-French three-factor αs and factor loadings on portfolios independently sorted on product market competition and gross profitability. Product market competition is measured by the Herfindahl-Hirschman Index (HHI) in Hoberg and Phillips (2010). Gross profitability is defined as revenue minus cost of goods sold scaled by total assets [(REVT-COGS)/AT]. In June of each year t, NYSE, Amex, and Nasdaq stocks are sorted into three groups based on the tercile of the ranked values of HHI in year $t-1$. Independently, stocks are sorted into five groups based on the quintile of the ranked values of gross profitability in year $t-1$. Monthly returns on the resulting fifteen portfolios are then calculated from July of year t to June of year $t+1$. Monthly portfolio abnormal returns and factor loadings are computed by running time series regression of portfolio excess returns on Fama-French three-factor model. The sample period is from July 1976 to June 2007. The excess returns and αs are in percentages, and the t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error with three lags.

	HHI_L				HHI_M				HHI_H				$HHI_L - HHI_H$
	$Prof_L$	$Prof_3$	$Prof_H$	$H-L$	$Prof_L$	$Prof_3$	$Prof_H$	$H-L$	$Prof_L$	$Prof_3$	$Prof_H$	$H-L$	$H-L$
R^{ex}	0.00	0.55	0.97	0.97	0.38	0.78	0.76	0.38	0.55	0.58	0.69	0.14	0.82
	0.00	1.63	2.83	3.58	1.10	2.68	3.01	1.58	2.03	2.43	2.74	0.68	3.10
α	-0.76	-0.20	0.50	1.25	-0.34	0.13	0.48	0.82	-0.38	-0.19	0.19	0.57	0.69
	-3.62	-1.25	3.12	4.50	-2.38	1.02	3.39	4.00	-2.36	-1.53	1.29	2.69	2.44
b	1.24	1.17	1.05	-0.18	1.18	1.06	0.80	-0.38	1.12	1.02	0.88	-0.24	0.05
	24.29	32.33	22.86	-2.58	32.67	25.72	21.67	-7.00	24.14	28.72	19.36	-4.14	0.69
s	0.35	0.34	0.19	-0.16	0.38	0.21	-0.20	-0.58	0.08	-0.01	-0.12	-0.21	0.05
	4.23	4.79	2.28	-1.43	6.62	3.80	-3.69	-7.53	1.38	-0.21	-1.98	-2.98	0.46
h	-0.21	-0.14	-0.54	-0.33	-0.25	-0.13	-0.39	-0.14	0.55	0.38	-0.01	-0.55	0.22
	-1.79	-1.66	-5.89	-2.11	-4.05	-2.12	-5.35	-1.37	7.57	5.36	-0.11	-5.42	1.74

Table 3: Fama and MacBeth regressions of future returns on competition and gross profitability

This table reports results from Fama and MacBeth regressions of returns on gross profitability, product market competition, the interaction term between profitability and competition, and controls. Controls include book-to-market ($log(B/M)$), size ($log(ME)$), and past performance measured at horizons of one month ($r_{1,0}$) and twelve to two months ($r_{12,2}$). Independent variables are trimmed at the 1% and 99% levels. The sample period is from July 1976 to June 2007. The slope estimates are reported after times 100, and the t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error with three lags.

Proxy	GPA	Proxy	Interaction	$log(B/M)$	$log(ME)$	$r_{1,0}$	$r_{12,2}$
Fitted HHI	1.71	2.93	-11.80	0.51	-0.09	-4.89	0.86
	4.21	0.94	-2.46	5.34	-1.59	-10.63	5.82
Comp	0.71	-0.34	0.75	0.51	-0.09	-4.90	0.86
	3.07	-2.40	2.72	5.24	-1.66	-10.59	5.76

Table 4: IST-risk exposures

This table presents the IST-risk exposures for profitability portfolio returns in competitive and concentrated industries. Portfolio annual returns are regressed on IMC portfolio returns. Factor loadings and Newey-West t-statistics are reported. Panel A adopts ROE and fitted HHI measures. ROE is calculated as quarterly net income divided by one-quarter-lagged book-equity. Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (RDQ). Fitted HHI is measured as in Hoberg and Phillips (2010). Panel B uses ROA and fitted HHI measures. ROA is defined as quarterly net income divided by one-quarter-lagged assets. Panel C follows GPA and fitted HHI measures. GPA is defined as revenue minus cost of goods sold scaled by total assets. Panel D uses GPA and Compustat HHI. Compustat HHI is computed based on the sales market share from Compustat of each firm in the industry. The sample period for Panel A, B, and C is from 1977 to 2006. The sample period for Panel D is from 1965 to 2015.

	HHI_L				HHI_M				HHI_H				$HHI_L - HHI_H$
	$Prof_L$	3	$Prof_H$	$H-L$	$Prof_L$	3	$Prof_H$	$H-L$	$Prof_L$	3	$Prof_H$	$H-L$	$H-L$
Panel A: ROE and Fitted HHI													
β^{IMC}	1.66	0.95	0.74	-0.92	1.43	0.84	0.33	-1.11	0.44	-0.05	-0.06	-0.50	-0.42
	5.83	4.99	5.53	-3.74	6.81	4.35	1.95	-7.43	1.69	-0.38	-0.35	-2.54	-2.44
Panel B: ROA and Fitted HHI													
β^{IMC}	1.44	0.27	0.37	-1.06	1.14	0.73	0.45	-0.69	0.32	0.01	-0.07	-0.40	-0.49
	6.82	1.32	2.63	-9.17	4.87	3.44	2.79	-4.87	1.27	0.04	-0.49	-2.40	-2.21
Panel C: GPA and Fitted HHI													
β^{IMC}	1.45	0.74	1.14	-0.31	1.40	0.59	0.33	-1.07	0.11	-0.15	-0.12	-0.23	-0.07
	4.21	3.85	3.89	-0.57	7.81	3.58	1.81	-6.90	0.55	-1.10	-0.71	-1.35	-0.16
Panel D: GPA and Compustat HHI													
β^{IMC}	1.24	0.80	0.36	-0.88	0.83	0.22	0.61	-0.21	0.46	0.20	0.22	-0.23	-0.64
	6.25	5.48	2.23	-4.82	4.01	0.81	3.71	-1.02	3.00	1.14	1.53	-1.71	-3.09

Table 5: Linear SDF test

This table reports empirical estimates of γ_x and γ_z from the model SDF: $m = a - \gamma_x \Delta x - \gamma_z \Delta z$. I proxy for IST shocks$\Delta z$ with IMC portfolio returns; for the disembodied shock Δx with market portfolio returns. I use either profitability quintile portfolios in both competitive and concentrated industries terciles or profitability quintile portfolios in competitive industries tercile as test portfolios. I report first-stage estimates and Newey-West t-statistics with three legs; the mean squared errors (MSE); and mean absolute pricing errors (MAPE). The sample period is from 1977 to 2006 at annual frequency.

	10 GPA and Comp		5 GPA in High Comp	
	CAPM	MKT + IMC	CAPM	MKT + IMC
γ_x	0.37	0.5	0.33	1.14
	2.82	6.94	2.20	1.86
γ_z		-0.36		-1.42
		-1.81		-2.61
MAPE (%)	2.34	1.53	3.14	1.63
MSE (%)	3.20	2.39	4.01	1.97

Table 6: Parameters

This table summarizes the calibrated parameter values.

Parameter	Symbol	Value
Technology		
Growth rate of x-shock	μ_x	0.25%
Volatility of x-shock	σ_x	8.1%
Growth rate of IST shock	μ_z	0.1%
Volatility of IST shock	σ_z	3.9%
Mean-reversion parameter of project-specific shock	θ_u	0.03
Volatility of project-specific shock	σ_u	0.6
Production		
Project DRS parameter	α	0.9
Profit margin of investment firms	ϕ	7.5%
Depreciation rate of capital	δ	10%
Price elasticity of demand for highly competitive industries	ν_{comp}	18
Price elasticity of demand for medium competitive industries	ν_{med}	5
Price elasticity of demand for monopoly industries	ν_{mono}	1.2
Investment		
Maximum long-run project arrival rate	$\bar{\lambda}$	25
Minimum long-run project arrival rate	$\underline{\lambda}$	5
Project arrival rate in high-growth state	λ_H	10
Transition probability into high-growth state	μ_H	0.01
Transition probability into low-growth state	μ_L	0.1
SDF		
Risk-free rate	r	3%
Price of risk of x-shock	b_x	2
Price of risk of IST shock	b_z	-0.7

Table 7: Calibration moments

This table compares sample moments to moments in simulated data. Both firm-specific profitability and investment data are estimated using Compustat data, where I report time series averages of the median and interquintile range (IQR) of the investment rate and cash flows over capital, as well as median serial correlation of them across firms. Model moments are median estimates across 100 simulations, each with 2,000 firms and length of 50 years.

Moment	Competitive Economy		Concentrated Economy	
	Data	Model	Data	Model
Cash flows-to-capital, median	0.11	0.67	0.15	2.07
Cash flows-to-capital, IQR	0.75	0.65	0.25	0.35
GPA, serial correlation	0.85	0.88	0.90	0.90
Firm investment rate, median	0.14	0.10	0.12	0.08
Firm investment rate, IQR	0.28	0.20	0.17	0.18
Firm investment rate, serial correlation	0.29	0.37	0.36	0.41

Table 8: Profitability premium, simulated data

This table replicates the profitability premium across different industries of competition in simulated data. Decile portfolios are sorted on profitability to assets, defined as earnings (E_{ft}) over the replacement value of capital (B_{ft}). I report monthly value-weighted average portfolio returns and IST risk exposures. I report median estimates across 100 simulations, each with 2,000 firms and length of 50 years.

Data													
	HHI_L				HHI_M				HHI_H				$HHI_L - HHI_H$
	$Prof_L$	$Prof_3$	$Prof_H$	H-L	$Prof_L$	$Prof_3$	$Prof_H$	H-L	$Prof_L$	$Prof_3$	$Prof_H$	H-L	H-L
R^{ex}	0.05	0.64	1.15	1.10	0.25	0.67	0.66	0.41	0.56	0.58	0.70	0.14	0.96
β^{IST}	1.24	0.80	0.36	-0.88	0.83	0.22	0.61	-0.21	0.46	0.20	0.22	-0.23	-0.64
Model													
	HHI_L				HHI_M				HHI_H				$HHI_L - HHI_H$
	$Prof_L$	$Prof_M$	$Prof_H$	H-L	$Prof_L$	$Prof_M$	$Prof_H$	H-L	$Prof_L$	$Prof_M$	$Prof_H$	H-L	H-L
R^{ex}	0.29	0.73	0.86	0.57	1.05	1.25	1.29	0.24	1.32	1.33	1.33	0.01	0.56
β^{IST}	4.66	2.74	2.16	-2.51	1.31	0.44	0.24	-1.07	0.14	0.08	0.08	-0.05	-2.46

Table 9: Investment response to IST shock: profitability and competition alone

This table shows the differential response of investment of firms with different profitability or industry competition on measures of the IST shock, shocks to equipment price, and returns to the IMC portfolio $\triangle z \in \{\triangle z^I, R^{imc}\}$, with all right-hand-side variables normalized to unit standard deviation. Competitive industries refer to the lowest fitted HHI tercile. Concentrated industries refer to the highest fitted HHI tercile. I show the estimated coefficients $b_1 ... b_5$ from Equation (26), along with t-statistics computed using standard errors clustered by firm and year. I control for firm fixed effects and lagged investment. The sample is period is from 1977 to 2006.

	Profitability		Competition	
I/K_{ft}	IMC	$\triangle z^I$	IMC	$\triangle z^I$
$\triangle z_{t-1}$	2.19	0.70	2.98	0.79
	3.44	1.62	7.17	1.47
$D(G_f)_2 \times \triangle z_{t-1}$	-1.29	-0.56	-2.15	-0.98
	-1.58	-1.66	-7.47	-1.72
$D(G_f)_3 \times \triangle z_{t-1}$	-1.16	-0.83	-1.83	-0.78
	-1.43	-2.09	-6.32	-2.10
$D(G_f)_4 \times \triangle z_{t-1}$	-1.38	-0.75	-2.28	-1.05
	-1.34	-1.71	-4.23	-1.54
$D(G_f)_5 \times \triangle z_{t-1}$	-1.05	-0.98	-2.52	-0.80
	-1.04	-2.40	-6.51	-1.79

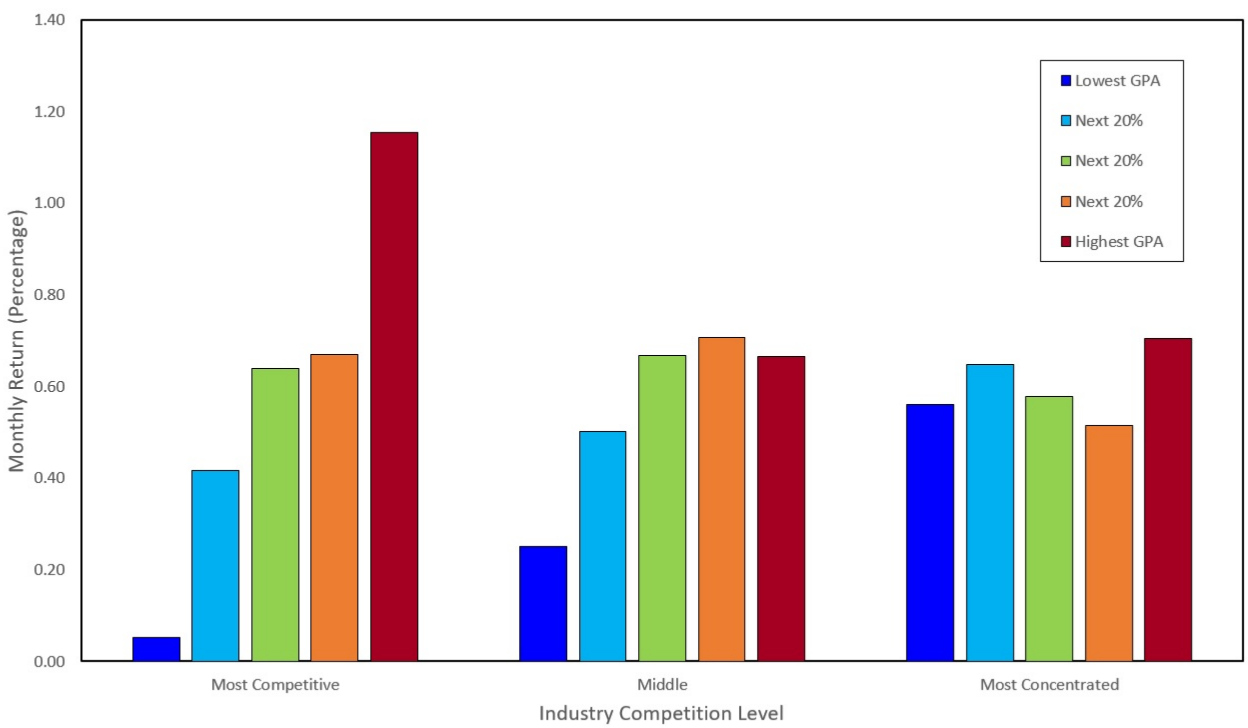
Table 10: Investment response to IST shock: profitability and competition

This table shows the differential response of investment of firms with different profitability in competitive and concentrated industries on measures of the IST shock, shocks to equipment price, and returns to the IMC portfolio $\triangle z \in \{\triangle z^I, R^{imc}\}$, with all right-hand-side variables normalized to unit standard deviation. Competitive industries refer to the lowest fitted HHI tercile. Concentrated industries refer to the highest fitted HHI tercile. I show the estimated coefficients $b_1 ... b_5$ from Equation (26), along with t-statistics computed using standard errors clustered by firm and year. I control for firm fixed effects and lagged investment. The sample is period is from 1977 to 2006.

	Competitive industries		Concentrated industries	
I/K_{ft}	IMC	$\triangle z^I$	IMC	$\triangle z^I$
$\triangle z_{t-1}$	4.97	2.31	0.73	-0.36
	4.38	2.45	2.19	-0.84
$D(G_f)_2 \times \triangle z_{t-1}$	-3.49	-1.79	-0.44	0.57
	-2.56	-2.28	-1.25	1.13
$D(G_f)_3 \times \triangle z_{t-1}$	-3.53	-1.85	-0.18	0.39
	-2.93	-2.17	-0.46	1.31
$D(G_f)_4 \times \triangle z_{t-1}$	-3.34	-2.26	-0.50	0.85
	-2.47	-2.31	-1.36	1.71
$D(G_f)_5 \times \triangle z_{t-1}$	-3.33	-2.56	-0.14	0.67
	-2.60	-2.77	-0.29	1.56

Figure 1. Monthly Average Excess Returns of Portfolios Sorted by Competition and Profitability

This figure plots the average monthly excess return on portfolios formed in a 3 × 5 sort that ranks first by industry competition level and then by gross profitability. The sample period covers from July 1976 to June 2007.



Appendix: Tables for Additional Robustness Checks

Table A1: Portfolios conditionally sorted by competition and ROE

This table reports the mean value-weighted returns and Fama-French three-factor αs and factor loadings on portfolios conditionally sorted on product market competition and return on equity (ROE). Product market competition is measured by the Herfindahl-Hirschman Index (HHI) in Hoberg and Phillips (2010). ROE is quarterly net income divided by one-quarter-lagged book-equity. Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (RDQ). At the beginning of each month, NYSE, Amex, and Nasdaq stocks are first sorted into three groups based on the tercile of the ranked values of HHI, and then sorting stocks within each tercile into five groups based on the quintile of the ranked values of ROE. Monthly returns on the resulting fifteen portfolios are then calculated from July of year t to June of year $t+1$. Monthly portfolio abnormal returns and factor loadings are computed by running time series regression of portfolio excess returns on Fama-French three-factor model. The sample period is from March 1975 to May 2006. The excess returns and αs are in percentages, and the t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error with three lags.

	HHI_L				HHI_M				HHI_H				$HHI_L - HHI_H$
	$Prof_L$	$Prof_3$	$Prof_H$	H-L	$Prof_L$	$Prof_3$	$Prof_H$	H-L	$Prof_L$	$Prof_3$	$Prof_H$	H-L	H-L
R^{ex}	-0.33	0.46	0.72	1.05	0.33	0.59	0.70	0.37	0.39	0.62	0.72	0.33	0.72
	-0.66	1.32	2.34	3.40	0.78	1.97	2.71	1.33	1.46	2.87	3.05	1.67	2.42
α	-1.16	-0.24	0.11	1.27	-0.41	-0.05	0.28	0.69	-0.52	-0.17	0.11	0.63	0.64
	-4.43	-1.43	0.86	4.44	-1.88	-0.35	2.66	2.98	-3.18	-1.84	0.99	3.23	2.28
b	1.32	1.09	1.10	-0.22	1.12	1.11	0.95	-0.17	1.03	0.97	0.97	-0.06	-0.16
	18.67	28.60	29.33	-2.86	16.58	30.15	36.41	-2.37	22.46	41.02	29.89	-1.17	-2.29
s	0.72	0.44	0.17	-0.56	0.69	0.09	-0.15	-0.84	0.24	0.01	-0.19	-0.43	-0.13
	7.27	8.07	2.65	-5.28	6.63	1.85	-3.63	-8.85	3.21	0.23	-4.16	-6.09	-1.26
h	-0.51	-0.29	-0.31	0.20	-0.40	-0.20	-0.33	0.07	0.43	0.39	0.12	-0.31	0.51
	-3.59	-2.84	-5.29	1.32	-3.77	-3.16	-7.92	0.74	5.82	8.86	1.71	-3.04	4.00

Table A2: Portfolios conditionally sorted by competition and ROA

This table reports the mean value-weighted returns and Fama-French three-factor αs and factor loadings on portfolios conditionally sorted on product market competition and return on assets (ROA). Product market competition is measured by the Herfindahl-Hirschman Index (HHI) in Hoberg and Phillips (2010). ROA is quarterly net income divided by one-quarter-lagged assets. Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (RDQ). At the beginning of each month, NYSE, Amex, and Nasdaq stocks are first sorted into three groups based on the tercile of the ranked values of HHI, and then sorting stocks within each tercile into five groups based on the quintile of the ranked values of ROA. Monthly returns on the resulting fifteen portfolios are then calculated from July of year t to June of year $t+1$. Monthly portfolio abnormal returns and factor loadings are computed by running time series regression of portfolio excess returns on Fama-French three-factor model. The sample period is from March 1975 to May 2006. The excess returns and αs are in percentages, and the t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error with three lags.

	HHI_L				HHI_M				HHI_H				$HHI_L - HHI_H$
	$Prof_L$	$Prof_3$	$Prof_H$	H-L	$Prof_L$	$Prof_3$	$Prof_H$	H-L	$Prof_L$	$Prof_3$	$Prof_H$	H-L	H-L
R^{ex}	-0.23	0.50	0.72	0.95	0.35	0.75	0.69	0.34	0.43	0.66	0.66	0.24	0.71
	-0.47	1.51	2.31	3.09	0.83	2.47	2.65	1.19	1.53	2.98	2.88	1.19	2.43
α	-1.10	-0.25	0.15	1.25	-0.38	0.04	0.29	0.67	-0.56	-0.15	0.10	0.65	0.60
	-4.21	-1.59	1.18	4.53	-1.78	0.29	2.63	2.89	-3.61	-1.52	0.86	3.48	2.20
b	1.35	1.15	1.07	-0.29	1.13	1.12	0.95	-0.18	1.07	0.99	0.93	-0.14	-0.14
	18.79	31.28	31.29	-3.72	18.09	27.83	34.72	-2.74	27.06	41.65	28.98	-3.06	-2.03
s	0.76	0.32	0.16	-0.60	0.69	0.08	-0.14	-0.83	0.28	-0.03	-0.18	-0.46	-0.14
	7.48	6.06	2.73	-5.96	7.83	1.50	-3.39	-10.05	3.88	-0.84	-3.83	-6.89	-1.42
h	-0.49	-0.17	-0.37	0.12	-0.43	-0.08	-0.36	0.07	0.49	0.43	0.07	-0.42	0.54
	-3.41	-1.80	-6.36	0.80	-4.08	-1.12	-8.41	0.70	7.09	8.36	1.05	-4.20	4.39

Table A3: Portfolios conditionally sorted by Compustat HHI and gross profitability

This table reports the mean value-weighted returns and Fama-French three-factor αs and factor loadings on portfolios conditionally sorted on product market competition and gross profitability. Product market competition is measured based on the sales market share from Compustat of each firm in the industry. Gross profitability is defined as revenue minus cost of goods sold scaled by total assets [(REVT-COGS)/AT]. In June of each year t, NYSE, Amex, and Nasdaq stocks are first sorted into three groups based on the tercile of the ranked values of HHI in year $t-1$, and then sorting stocks within each tercile into five groups based on the quintile of the ranked values of gross profitability in year $t-1$. Monthly returns on the resulting fifteen portfolios are then calculated from July of year t to June of year $t+1$. Monthly portfolio abnormal returns and factor loadings are computed by running time series regression of portfolio excess returns on Fama-French three-factor model. The sample period is from July 1964 to December 2015. The excess returns and αs are in percentages, and the t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error with three lags.

	HHI_L				HHI_M				HHI_H				$HHI_L - HHI_H$
	$Prof_L$	$Prof_3$	$Prof_H$	H-L	$Prof_L$	$Prof_3$	$Prof_H$	H-L	$Prof_L$	$Prof_3$	$Prof_H$	H-L	H-L
R^{ex}	0.30	0.46	0.82	0.52	0.36	0.50	0.67	0.31	0.61	0.58	0.61	0.00	0.52
	1.00	2.16	4.17	2.28	1.45	2.36	3.15	1.81	2.77	2.77	2.85	-0.01	2.19
α	-0.24	0.02	0.55	0.78	-0.34	-0.04	0.32	0.65	-0.01	0.01	0.14	0.15	0.64
	-1.39	0.22	5.72	3.76	-3.19	-0.42	3.19	4.21	-0.05	0.16	1.37	0.94	2.89
b	1.18	1.01	0.89	-0.30	1.22	1.03	0.92	-0.30	1.09	1.00	0.93	-0.15	-0.14
	25.74	34.24	32.39	-5.17	34.23	34.65	35.85	-6.68	32.68	41.78	24.05	-2.77	-2.36
s	0.31	0.00	-0.17	-0.47	0.09	0.07	0.01	-0.08	0.00	0.14	0.11	0.11	-0.58
	4.12	0.04	-3.96	-5.38	1.82	1.39	0.30	-1.24	0.07	4.07	1.82	1.60	-6.86
h	-0.34	-0.17	-0.35	-0.02	0.26	0.07	-0.29	-0.55	0.26	0.13	-0.05	-0.31	0.30
	-3.99	-4.14	-6.02	-0.14	4.86	1.21	-6.94	-7.69	4.98	3.52	-0.77	-3.45	2.62