Product Market Competition and Industry Returns*

M. CECILIA BUSTAMANTE and ANDRÉS DONANGELO†

ABSTRACT

This paper documents that product market competition has two opposing effects on asset returns. We find that firms in more competitive industries have less valuable growth options and thus lower loadings on systematic risk. We also find that these firms have lower profit margins which make them more exposed to systematic shocks. The first effect dominates the second, so that firms in more competitive industries earn lower asset returns on average. Our empirical findings are robust to using five alternative empirical measures of competition, and to controlling for the sample selection bias of publicly listed firms.

*This version: October 2013.

†Cecilia is with the Department of Finance, London School of Economics, and Andrés is with the Finance Department, University of Texas at Austin. We thank Andrés Almazan, Aydogan Alti, Christian Julliard, Lorenzo Garlappi, Thomas Gilbert, Daniel Paravisini, Veronica Rappoport, Xiaoji Lin, Sheridan Titman, and seminar participants at the Minnesota Asset Pricing Mini-Conference, UT Austin, Western Finance Association's 2013 Meetings, European Finance Association's 2013 Meetings, and University of Rochester. All errors are our own.

A stock price represents the expected discounted value of the future stream of cash flows that belong to the shareholders of a firm. The competitive environment in which a firm operates determines both the level and the riskiness of its cash flows. Despite the economic relevance of product market competition, there has been no conclusive empirical evidence on its unconditional effect on stock returns. A likely reason for this gap in the literature is that product market competition is difficult to measure. This paper proposes a comprehensive approach that overcomes this challenge, and shows that firms in highly competitive industries generally earn lower asset returns. Moreover, our methodology unveils the mechanism through which competition affects firms' exposure to systematic risk. We provide evidence that most significant channel through which product market competition affects asset returns is through its impact on firms' investment decisions.

We hypothesize that product market competition affects expected asset returns through two main channels.[1] The first channel is related to the relative weight of growth options on firm value. We denote this the "investment channel". This is consistent with the theoretical prediction that competition erodes the value of growth options. For this reason, firms in more competitive industries have higher earnings-to-price and book-to-market ratios. The second channel through which product market competition affects expected asset returns is related to cash flows. We denote this the "operating leverage channel". This channel relates to the fact that firms in more competitive industries have lower profit margins which buffer shocks to the firm. For this reason, product market competition leads to higher levels of operating leverage.[2]

The investment and operating leverage channels have opposing effects on expected asset returns. On the one hand, product market competition decreases a firm's risk exposure by lowering the value of its growth options. The value destruction due to threat of entry or expansion by competitors is pro-cyclical, which effectively lowers expected returns in more competitive industries. On the other hand, product market competition increases expected returns by amplifying operating leverage. The net effect of product market competition on expected returns depends of the relative importance of the two channels. Our empirical results provide supporting evidence that the investment channel dominates the operating leverage channel, such that product market competition effectively reduces average asset returns.

The empirical analysis of these hypotheses is challenging insofar product market competition

[1] These two channels are consistent with the models in Grenadier (2002) and Aguerrevere (2009).

[2] We define operating leverage as the degree of sensitivity of operating profits to shocks.

is not directly observable, and that there is no consensus on the best way of proxying for it. We address this challenge with a comprehensive approach. We use five alternative measures of imperfect product market competition (IPMC). Our first two measures of IPMC are the widely used Herfindahl-Hirshman Index (HHI) and average industry markup. These two base measures proxy for the two different telltales of IPMC: concentration and market power. We construct the HHI and the average industry markup using U.S. Census data. Census-based measures of IPMC are known to dominate measures solely based on publicly listed firms (e.g., based on the Compustat dataset).[3]

A limitation of U.S. Census measures of IPMC is that they only cover manufacturing industries, and are only available for the last three decades. To address this issue, we propose a new measure of IPMC. We expand the cross-sectional width and length of our panel by constructing a new measure of industry concentration based on Compustat data that covers both manufacturing and non-manufacturing industries. The use of data on publicly listed firms to estimate industry competition is problematic, as the sample of publicly listed firms is not randomly selected.[4] Our first proposed new measure, which we denote "Characteristic-Based Concentration (CBC)", relies on Compustat sales data of public firms adjusted for the likelihood of observing public firms in each industry. To the best of our knowledge, this is the first measure of industry competition based on publicly-listed firm data that incorporates the observation that the sample of publicly listed firms is not random.

An additional concern is that markup and industry concentration need not capture competition accurately in industries with differentiated products or price wars. To address this issue, we propose another measure of IPMC which we denote "Concentration and Markup Combined" (CMC). This measure aggregates the two most commonly used proxies of PMC: industry concentration and the average industry markup. Finally, we consider the firm-specific text-based measure by Hoberg and Phillips (2010b).[5] This measure uses the product descriptions available in the 10-K filings of public firms to determine their closest competitors. The use of this fifth measure addresses the traditional concern in the industrial organization literature that market shares and markups are endogenous outcomes of competition.

[3]See Ali, Klasa, and Yeung (2009) for a discussion on the importance of using U.S. Census data when measuring industry concentration.

[4]For instance, the listing requirements of stock exchanges require a minimum firm size. This implies that publicly listed firms are usually larger than their private peers in the industry.

[5]We are grateful to Gerard Hoberg and Gordon Phillips for making data with the measure available online.

Furthermore, our empirical approach takes into account that even if product market competition were easily measurable, we only observe the market prices and stock returns of the publicly listed firms in each industry. The use of a subsample of public firms would not be a problem if systematic differences between the public and private firms within industries were unrelated to product market competition. Yet the empirical evidence suggests that a firm's public status is significantly influenced by the competitive environment. For instance, Chemmanur, He, and Nandy (2010) document that the decision to go public is significantly affected by the product market. We thus control for the sample selection bias of public listing in our empirical tests. To our understanding, our paper is the first to highlight the possibility of biased inferences about the link between asset prices and any industry characteristic when firms' public status is significantly influenced by such industry aspect.

Using portfolio sorts and panel data regressions with year effects, we report that one-year-ahead returns and conditional market betas are higher in less competitive industries. These results are robust to the use of all five alternative measures of IPMC. This finding is in contrast with that by Hou and Robinson (2006), who report that stock returns are negatively related to Compustat-based measures of industry concentration. This difference in empirical results suggests that considering both private and public firms is important to study the link between product market competition and expected returns.

We also find empirical support for the two channels in which product market competition affects asset returns. Consistent with the investment channel, our results show that firms in more competitive industries have higher earnings-to-price and book-to-market ratios. Moreover, we find that the contribution of growth options on market betas is increasing in all IPMC measures. Consistent with the operating leverage channel, we find that firms in industries with with levels of product market competition have higher measures of operating leverage. Our results show that the contribution of assets in place on market betas is decreasing in all IPMC measures.[6]

The testable hypotheses of our paper relate closely to the models of oligopoly by Grenadier (2002) and Aguerrevere (2009). In particular, Aguerrevere (2009) predicts that firms in less competitive industries earn higher expected returns when demand is high, and lower returns otherwise. We reformulate this conditional implication into an unconditional one in our empirical tests where

[6]To assess the link between product market competition and our two channels, we decompose market betas into betas of assets in place and betas of growth options using an extension of the methodology proposed by Bernardo, Chowdhry, and Goyal (2007).

we hypothesize the investment channel is stronger in less competitive industries.[7]

The evidence in our paper relates to the growing empirical literature studying the impact of competitive pressures on firms' value and exposure to risk. We contribute to the discussions by Hou and Robinson (2006) and Ali, Klasa, and Yeung (2009), as we document the unconditional effect of product market competition on industry returns using a comprehensive empirical approach. Our findings also relate to Hoberg and Phillips (2010a), who note that product market competition has a significant effect on asset prices. Hoberg and Phillips (2010a) document that average industry returns are more predictable in more competitive industries.

The evidence on the investment channel relates to the empirical literature on the effects of competitive pressures on investment policies. The finding that firms in more competitive industries have higher earnings-to-price ratios is consistent with Bulan, Mayer, and Somerville (2009). Their study uses data of real estate developments to show that competition erodes growth option values. Our paper also relates to Frésard and Valta (2013), who argue that competition has a significant effect on corporate investment using a sample of Compustat firms.

The evidence on the operating leverage channel relates to the finance literature on operating leverage. Novy-Marx (2011) documents that operating leverage increases firms' risk exposure. We contribute to his work as we document that operating leverage is higher and contributes more significantly to the riskiness of firms in more competitive industries. Our results are also consistent with Ortiz-Molina and Phillips (2013). They report that firms with more illiquid assets have a higher cost of capital, and that this effect is stronger in more competitive industries.

Lastly, we add to the empirical literature exploring differences in the risk-return profiles of public and private firms. In particular, our paper relates to the recent study by Cooper and Priestley (2013) on the riskiness of private firms. As a by-product of our empirical approach, we provide evidence that privately listed firms are significantly riskier, have lower earnings-to-price ratios and lower book-to-market ratios than publicly listed firms.

The rest of the paper proceeds as follows. Section I elaborates on the main testable predictions of our paper. Section II describes the empirical strategy, and the summary statistics of our working database. Section III provides the supporting empirical evidence. Section IV concludes.

[7] Other related theoretical papers include Garlappi (2004), Dockner, Carlson, Fisher, and Giammarino (2011), Bena and Garlappi (2011) and Bustamante (2012). While this literature focuses on the effect of intra-industry interactions on investment and expected returns, we focus instead the cross section of average industry returns. The recent model by Loualiche (2013) also relates to our paper, insofar it elaborates on the impact of entry by new firms on asset prices.

I. Hypothesis Development

This section discusses the role of product market competition on firm value and risk exposure.[8] We start by considering a firm that operates in an industry. The industry represents the competitive environment in which the firm operates. In particular, the price of the good produced by the firm is inversely related to total production in the industry. This feature is consistent with a downward sloping demand curve, and implies that firms in the industry affect each other through production decisions.

The expected value of any firm in the industry can be decomposed into the expected value of cash flows generated by such firm when there are no changes in the capacity of the industry, and the future expected value of the firm related to changes in industry capacity, i.e. $V = V^{\mathrm{A}} + V^{\mathrm{G}}$. We denote the first component of firm value (V^{A}) by "value of assets in place". We denote the second component (V^{G}) by "value of growth options", although one should keep in mind that it represents the value of future expected capacity changes by the firm *and* by its competitors. To discuss the role of product market competition on operating leverage, we can further decompose the expected value of assets in place into the expected value of variable cash flows (V^{AV}), i.e. revenues and variable operating costs, and the expected value of fixed costs ($-V^{\mathrm{AF}}$), i.e. $V^{\mathrm{A}} = V^{\mathrm{AV}} - V^{\mathrm{AF}}$. The expected value of the firm can thus be decomposed into three mutually exclusive parts:

$$V = V^{\mathrm{AV}} - V^{\mathrm{AF}} + V^{\mathrm{G}}. \tag{1}$$

A firm's exposure to systematic risk (β) can be expressed in terms of the riskiness of each of the components of firm value in Equation (1), which we denote β^{AV}, β^{AF}, and β^{G}. In fact, β is the weighted average of the β^{AV}, β^{AF}, and β^{G}, namely

$$\beta = \frac{V^{\mathrm{AV}}}{V}\beta^{\mathrm{AV}} - \frac{V^{\mathrm{AF}}}{V}\beta^{\mathrm{AF}} + \frac{V^{\mathrm{G}}}{V}\beta^{\mathrm{G}}. \tag{2}$$

In the short run, one can expect fixed operating costs to be approximately unaffected by systematic shocks, such that $\beta^{\mathrm{AF}} = 0$. After making this assumption and rearranging terms in Equation (2),

[8] Our argument is consistent with existing models in the literature (e.g., those in Grenadier (2002) and Aguerrevere (2009)). For this reason, we briefly discuss our hypotheses in this section and provide a more formal treatment in the Appendix. Appendix A presents a model of an industry equilibrium consistent with our testable implications.

we obtain

$$\beta = \beta^{\mathrm{G}} - \frac{V^{\mathrm{A}}}{V}\left(\beta^{\mathrm{G}} - \beta^{\mathrm{AV}}\left(1 + \frac{V^{\mathrm{AF}}}{V^{\mathrm{A}}}\right)\right). \tag{3}$$

Note that the ratio $\frac{V^{\mathrm{AF}}}{V^{\mathrm{A}}}$ represents the weight of fixed operating costs relative to the value of current assets. We denote this ratio as "operating leverage" since the greater the fixed operating costs, the more sensitive operating profits will be to shocks to the firm.

Our testable hypotheses are based on the opposing effects of product market competition on the growth options and assets in place of the firm. We hypothesize that product market competition affects a firm's value and expected returns through its effect on the ratio of assets in place to total firm value, $\frac{V^{\mathrm{A}}}{V}$, and operating leverage, $\frac{V^{\mathrm{AF}}}{V^{\mathrm{A}}}$. In what follows, we use subscripts M and C to denote a firm in an industry with low levels of product market competition and a firm in an industry with high levels of PMC, respectively.[9] Our first testable hypothesis is related to the effect of product market competition on the relative value of assets in place:

Hypothesis 1. *The ratio of assets in place over total value is lower in firms in less competitive industries, than in otherwise identical firms in more competitive industries, such that*

$$\frac{V^{\mathrm{A}}_{\mathrm{M}}}{V_{\mathrm{M}}} < \frac{V^{\mathrm{A}}_{\mathrm{C}}}{V_{\mathrm{C}}}. \tag{4}$$

The intuition behind Hypothesis 1 is that product market competition erodes the growth option value of firms, which in turn makes assets in place relatively more valuable in industries with low competition.[10] A firm in a less competitive industry earns higher operating margins than an otherwise identical firm in a competitive industry. Moreover, as discussed above, a firm in a less competitive industry has more valuable growth options, so that $V_{\mathrm{M}} > V_{\mathrm{C}}$.

Hypothesis 1 is consistent with existing real options literature on competition. Grenadier (2002) shows that competition erodes the option value of waiting to invest. Leahy (1993) shows that the value of the value of future investment is effectively zero in the extreme case of perfect competition. An additional economic argument is that the value destruction due to expansion by

[9]Here "M" stands for "monopolistic" and "C" stands for "competitive".

[10]We express the hypothesis in terms of assets in place, and not of growth options, to make it consistent with our empirical tests. In particular, $\frac{V^{\mathrm{A}}}{V}$ is conceptually related to observable financial variables such as earnings-to-price and book-to-market ratios.

existing competitors or new entrants is larger in more competitive industries.[11].

Our second testable hypothesis is related to the effect of product market competition on the level of operating leverage:

Hypothesis 2. *All else being the same, the degree of operating leverage of firms in more competitive industries is greater than that of firms in a less competitive industries:*

$$\frac{V_{\mathrm{M}}^{\mathrm{AF}}}{V_{\mathrm{M}}^{\mathrm{A}}} < \frac{V_{\mathrm{C}}^{\mathrm{AF}}}{V_{\mathrm{C}}^{\mathrm{A}}}. \tag{5}$$

Hypothesis 2 states that the level of operating leverage is higher in more competitive industries. The intuition is that product market competition reduces the value of assets in place but should not greatly affect the value of fixed operating costs. Fixed operating costs are unrelated to systematic risk (i.e., $\beta^{\mathrm{AF}} = 0$) and should thus be discounted at the risk free rate in any industry. This implies that fixed operating costs carry a greater weight firm value in more competitive industries.

To discuss of the effect of product market competition on expected returns, we note that growth options are levered positions in future assets in place. As a result, it holds that $\beta^{\mathrm{G}} > \beta^{\mathrm{AV}}$. Equation (3) reveals that Hypotheses 1 and 2 have opposing effects on systematic risk loadings and thus on expected returns. On the one hand, the effect of product market competition on operating leverage (the "operating channel") increases expected returns. On the one hand, the effect of product market competition on the relative value of growth options (the "investment channel") increases expected returns when operating leverage is low.

Hypothesis 3. *All else being equal, the contribution of growth options to systematic risk loadings is decreasing in product market competition, while the corresponding contribution of operating leverage is increasing in product market competition.*

The statement of Hypothesis 3 highlights that the overall effect of product market competition on a firm's risk exposure is an empirical question. On the one hand, product market competition reduces a firm's exposure to risk through the investment channel. The value destruction of product market competition is procyclical, such that product market competition reduces a firm's exposure to risk. On the other hand, firms in more competitive have lower operating margins to buffer

[11] In Appendix A, we show that the value our broadly defined growth options becomes negative under perfect competition

productivity shocks. This implies that product market competition increases a firm's exposure to risk by amplifying its operating leverage.

II. Empirical Strategy

We hereby describe the empirical strategy to test the hypotheses in Section I. The empirical strategy relies on three main observations.

The first observation is that the value of a firm's assets in place and the value of a firm's operating costs are not directly observable. We make identifying assumptions which relate a firm's assets in place to the book value of its assets, and a firm's fixed operating costs to observable measures of operating costs. As we argue below, our methodology is consistent with previous studies in the literature.

The second observation is that the degree of imperfect product market competition (hereafter, IPMC) in an industry is not directly observable. Moreover, there is no consensus in the literature over a single best proxy for IPMC. We use alternative measures of IPMC to assess the robustness of our results.

Product market competition is affected by the whole universe of firms in a particular product market. To the best of our knowledge, the only comprehensive measures of IPMC are based on U.S. Census Bureau data and only available for manufacturing-based industries. As discussed in Hoberg and Phillips (2010a), however, a large fraction of the firms in the merged CRSP/Compustat (hereafter, MCC) sample belong to non-manufacturing industries. To expand our sample, we propose a measure of industry concentration based on observable public firm sales, adjusted for the sample selection bias of public listing.

The last observation which we account for in our empirical strategy is that even for the most comprehensive measure of IPMC, we only observe the financial data of publicly listed firms. The testable implications of our paper relate to IPMC and average industry returns, assuming that the returns of all firms in the industry are observable. Yet we only observe the returns for those firms that are publicly traded, and which are tracked in the merged MCC dataset. This is a concern given that the sample of publicly listed firms is not randomly selected. To address this problem, we consider a specification in which we correct for the sample selection bias of publicly-listed firms.

A. Data Sources

We define an industry as all the public and private firms within the same four-digit Standard Industrial Classification (SIC) code. All our empirical tests consider data at an annual frequency. The traditional measures of competition for manufacturing industries are based on the Census of Manufactures reports produced by the U.S. Census Bureau. For the years in between, the reported values of each competition measure, we follow the empirical practice of repeating the available values of previous and subsequent years for those years in which no Census data are available.[12]

We use the data from the Bureau of Economic Analysis (BEA), and the Comparative Effectiveness Research Program at the National Bureau of Economic Analysis (CER/NBER) for average industry characteristics including private and public firms. In particular, labor intensity is defined as the ratio of employment compensation divided by the industry value added net of taxes and subsidies. We compute the average industry characteristics of public firms only using the annual Compustat files.

Finally, we use financial and accounting data at annual frequency from the MCC database provided by WRDS. Using these datasets, we construct annualized stock returns and conditional market betas. The conditional market betas are computed following the methodology in Lewellen and Nagel (2006). Market returns are from Kenneth French's website. We provide additional details on the database construction in Appendix E.

B. Measuring assets in place and operating leverage

Hypothesis 1 implies that firms in more competitive industries have higher earnings to price ratios. More generally, however, Hypothesis 1 predicts that the ratio of assets in place to total firm value is higher in firms in more competitive industries. Since the value of a firm's assets in place are unobservable, we follow Novy-Marx (2011) and make the working assumption that the value of a firm's assets in place equals the book value of its assets. We thus identify the ratio of assets in place to total firm value with the book to market ratio of the firm. Given this identifying assumption, Hypothesis 1 also implies that firms in more competitive industries have higher book to market ratios.

[12] See, for instance, Ali, Klasa, and Yeung (2009) for an example of this practice.

Similarly, Hypothesis 2 predicts that firms in more competitive industries have higher operating leverage. Yet firms' fixed operating costs and their corresponding operating leverage are not directly observable. To make Hypothesis 2 testable, we follow two alternative strategies. We first construct a measure of operating leverage consistent with our definition in Section I. We run time-series regressions at the industry level of value added growth on total factor productivity growth using NBER/CER data for manufacturing industries. We use the slope of this regression as an industry measure of operating leverage.

Due to the poor coverage of this first measure, we also construct an empirical proxy for the ratio of the present value of fixed operating costs to total firm value following the methology in Novy-Marx (2011). Novy-Marx (2011) defines operating leverage as the ratio of the sum of firms' selling, general and administrative expenses and their costs of goods sold to total assets. The measure of by Novy-Marx (2011) is at the firm level, and also allows us to test more easily the asset pricing implications of the model.

We test the predictions in Hypothesis 3 given our working assumptions. In particular, we relate the portfolio weight of the riskiness of assets in place to its book to market ratio, and we relate the portfolio weight of the riskiness of operating leverage to the ratio of a firm's selling, general and administrative expenses and their costs of goods sold to total firm value.[13]

C. Measuring Product Market Competition

The level of product market competition in an industry is determined by the dynamic interaction between firms inside and outside the industry, productive technologies, suppliers, workers, and customers, as well as aggregate economic conditions. The complexity of product market competition and its intrinsically unobservable nature represents a challenge for the study of its effect on firm risk.

We partially address this problem by employing five alternative measures of IPMC. Two measures are based on U.S. Census data that only cover manufacturing based industries. Two additional constructed measures based also on Compustat data, that also cover non manufacturing industries in the MCC dataset. Lastly, we use the text-based competition measure by Hoberg and Phillips (2010b), which measures competition by considering product descriptions in firms' $10-K$ filings.

[13]We elaborate further on this in Section III.

C.1. IPMC measures based on U.S. Census data

Out of our five measures of IPMC, two of them are constructed using U.S. Census data and are available for manufacturing industries only. The first measure is the sales-based Herfindahl–Hirschman Index (HHI). This measure is the most commonly used in the recent finance literature on competition and firm risk (e.g., Ali, Klasa, and Yeung (2009) and Hoberg and Phillips (2010a)). The Census industry concentration measure or HHI is defined as:

$$HHI \equiv \frac{1}{N}\sum_{j=1}^{N} s_j^2, \tag{6}$$

where s_j is the market share of firm j on total industry sales. In the empirical tests and merely for rescaling purposes, we refer to HHI as the logarithm of (6).[14]

Our second IPMC measure is the average operating markup of the industry using the methodology in Ali, Klasa, and Yeung (2009) defined as:

$$markup \equiv \frac{\textit{Value of Sales} + \Delta\ \textit{Inventories - Payroll - Cost of Materials}}{\textit{Value of Sales} + \Delta\ \textit{Inventories}}. \tag{7}$$

The measure *Markup* is constructed from data from the annual CER/NBER files on aggregate industry characteristics. The measure is a noisy indicator of the Lerner index, which measures the market power of firms in an industry.

C.2. Characteristics-Based Concentration Measure

Given that a large fraction of firms in the MCC dataset belong to non-manufacturing industries, the use of the measures of competition described in the previous section would lead to a significant sample restriction. To extend our sample, we construct an alternative sales concentration measure, Characteristic-Based Concentration (CBC), for both manufacturing and non-manufacturing industries.

We construct the CBC measure based on two related economic arguments. The first is that

[14] As we elaborate below, our Characteristic-Based-Concentration measure or CBC is also defined in logs.

the industry sales concentration is a function of the mean and standard deviation of firms' sales in the industry.[15] The second argument is that we can adjust the industry means and variances of the sales of public firms reported in Compustat for the sample selection bias of public listing, and obtain a proxy for the average industry means and variances in the sales of public and private firms for all industries in the MCC dataset. We use these two economic arguments to construct a proxy of industry concentration for all industry-years in the MCC dataset, such that:

$$CBC = -ln(\hat{N}) + ln\left(\frac{\hat{\sigma}^2_{sales}}{\hat{\mu}^2_{sales}} + 1\right), \tag{8}$$

where we use the actual total number of firms N reported by the U.S. Census Bureau for manufacturing industries if available, and the proxy $\hat{N}$ otherwise.[16] We construct the CBC measure for all industry-years in the MCC dataset. Please see Appendix F for additional details on the construction of the CBC measure.

Panel A of Table I reports the bottom and top fifteen industries in our sample sorted by the CBC measure. The least competitive industries as ranked by the CBC include pharmaceuticals, biological research, airport services, petroleum refining, motion pictures, and drugs. This suggests that our CBC measure identifies least competitive firms in both manufaturing and non manufacturing industries.

Figure 1 validates the *CBC* measure by showing that it is significantly positively related to the *HHI* measure based on Census data. The figure shows a plot relating the sample averages of the two measures for manufacturing industries, over the entire sample period covered by *HHI*, 1982–2009. This is an interesting exercise since the construction of the *CBC* measure does not utilize data from the Census of Manufactures used in the *HHI* measure.

To put the result from Figure 1 in perspective, we also compare the relation between *HHI* measure and the Compustat-based sales HHI measured as in Hou and Robinson (2006). The figure shows that the relation between the logarithm of the Compustat HHI and the logarithm of the Census HHI is fairly flat which leads to an R^2 of 0.08. In contrast, the *CBC* has an R^2 of 0.23. This suggests that the adjustment for the sample selection bias of public listing is relevant in capturing

[15] It is straightforward to express the HHI of the industry as $HHI = \frac{1}{N}\left(\frac{\sigma^2_{\text{sales}}}{\mu^2_{\text{sales}}} + 1\right)$.

[16] Section D elaborates on the sample selection correction.

IPMC.[17]

C.3. Concentration-Markup Combined Measure

On average, we should expect industry concentration and average profit margins to be positively correlated across industries. In a perfectly competitive industry, both concentration and margins should be low since there are many firms with low market share and low operating markups. In a , the opposite holds: both concentration and margins are high since the single firm has high market share, which protects its high margins. In these cases, the *HHI*, *CBC*, and *Markup* measures should lead to the same ranking of industries.

Unfortunately, there are instances in which industry concentration and margins diverge. For instance, in an industry under monopolistic competition there are many firms producing highly differentiated products. In such an industry, concentration measures may be low, and yet firms have high makups due to their product differentiation which insulates them from competition. Another example in which concentration and markups diverge is the case of an industry facing a price war (i.e., Betrand competition). In this case, a possibly small number of firms fiercely compete away profit margins. Hence markups classify the industry as highly competitive, while industry concentration may be high.

We consider the fact that concentration and profit margins possibly contain orthogonal pieces of information about IPMC in a fourth measure of IPMC that combines concentration and profit margins. The measure is defined as the sum of the cross-sectional ranks (0 to 20) of *Markup* and *CBC* divided by 40.[18] For simplicity, we denote this measure as "Concentration-Markup Combined" (henceforth *CMC*).

Panel B of Table I reports the bottom and top fifteen industries in our sample sorted by the CMC measure. This measure only applies to manufacturing industries. Consistent with our analysis in Panel A for the CBC measure, this alternative measure also sorts pharmaceuticals and petroleum refining in the least competitive group. The CMC measure also reports cigarettes, computers, broadcasting and cosmetics in the least competitive group.

[17] Note that these figures consider average industry observations for the entire sample. The CBC measure is more significantly related to the Census HHI when we consider industry year observations. The pairwise correlation between the CBC and the Census HHI using industry year data is 32 per cent, and it is significant at the 1 per cent level.

[18] We verified that the results presented in the paper are robust to rank breakdowns of 0-5 and 0-10.

C.4. Text-Based Competition Measure

While both markups and concentration measures are heavily used to capture product market competition, they are subject to the criticism of endogeneity. More precisely, markups and market shares are by determined in equilibrium by firm's investment decisions, barriers to entry, macroeconomic conditions, etc. Another related concern is that both measures are based on the SIC as the primary industry classification method, which has been criticized in recent years. To address these concerns, we consider the firm-specific text-based measure of competition by Hoberg and Phillips (2010b). We denote this measure as "Text-Based Competition" (TBC).

Instead of using investment or market shares, the TBC measure relies on a firm's product description to determine its closest competitors. The industry classification method is based on firm pairwise similarity scores from product descriptions in firms' 10-K filings.[19] As a caveat, the TBC is only available for the time period 1996-2008. Furthermore, since the 10-K filings are only available for public firms, the TBC measure does not explicitly address the concern of the sample selection bias of public listing.

D. Sample Selection Correction

The last observation which we account for in our empirical strategy is that even for the most comprehensive measure of IPMC, we only observe the financial data of publicly listed firms. The testable implications of our paper relate to IPMC and average industry returns, which implicitly assumes that the returns of all firms in the industry are observable. Yet we only observe the returns for those firms that are publicly traded, and which are tracked in the merged MCC dataset. To address this problem, we also present our results corrected for the selection bias inherent in the subsample of publicly listed firms.

Theoretical work that relates industry properties to industry-specific average firm risk in the industry implicitly considers the whole universe of firms, both public and private. To illustrate the problem of sample selection when testing such theories, consider the relation between public firms'

[19] Just like SIC or NAICs industry classifications, this method assumes that membership in industries is transitive - if firm A is in firm B's industry and firm C is in firm B's industry, than firm A and C are in each other's industry. It can thus be used in the same way SIC or NAICS industry controls are used. See Hoberg and Phillips (2010b) for details.

beta, β, and the industry labor intensity $1-\alpha$. If the public status of firms in a given industry is unrelated to the degree of labor intensity, then the OLS regression of β on $1-\alpha$ provides unbiased estimates. However, if the labor intensity affects firms' decisions to be public, then the OLS regression of the β of public firms on $1-\alpha$ leads to a biased inference on how firms' exposure to systematic risk relates to labor intensity. To our knowledge, the empirical literature has not yet accounted for the fact that we only observe the returns for the subsample of the publicly listed firms, which is not randomly selected.

In the context of our working sample, Figure 2 illustrates that the public status of firms by industry is positively correlated with average returns and product market competition. This validates our concern to control for the sample selection bias o public listing in our empirical tests. Panels A and B suggest that industries with a higher share of public firms have higher returns and higher betas on average. Panel C shows that industries with a higher share of public firms are also less competitive. This can be explained by the fact that firms in less competitive industries are larger, and that the likelihood of being public is also increasing in size. Panel D suggests that the share of public firms in an industry is decreasing in market to book - i.e. public firms are value firms relative to their private peers.

We control for sample selection bias in our empirical tests using a two-stage empirical approach, as in Heckman (1979).

D.1. First Stage

In a first stage, we compute the probability that a firm is public as a function of industry-specific average characteristics. Given that we do not observe the characteristics of private firms at the firm level, we are unable to compute the probit model discussed in Heckman (1979). We thus compute the average probability that a firm is public in a given industry-year using an alternative empirical approach, which we explain in detail in Appendix F.[20] The underlying assumption of our empirical approach is that likelihood of being public can be explained by average industry characteristics, such as its labor intensity. We use the results of the first stage to compute an inverse Mills' ratio by industry-year λ.

[20]We estimate the probability of being public by industry-group using an empirical approach based on the approach discussed in Greene (1992) to test selection models using proportions data. See Appendix F.

D.2. Second Stage

In the second stage, we use the inverse Mills' ratio by industry-year λ to correct for the sample selection of public listing, in each of our OLS regressions of returns and betas on industry characteristics.

In our paper, the sign and significance of the coefficient on λ in these OLS regressions has an important economic interpretation. Anticipating, in all the regressions below, the inverse Mills' ratio λ is always highly significant and negatively related to betas or returns. This implies that, on average, unobserved private firms are riskier than public firms.

We also apply the sample selection correction to construct the CBC measure. We run OLS regressions of the logarithm of the sales of public firms in Compustat using an inverse Mills ratio by industry-year, which controls for the probability of observing that firm in the sample. We use the results of these regressions to construct the adjusted average sales for public and private by industry-year, $\hat{\mu}_{sales}$, and the adjusted industry variance in sales of public and private firms by industry-year, $\hat{\sigma}_{sales}$.[21] We elaborate on the details of the sample selection correction in Appendix F.

E. Summary Statistics Sorted on Measures of Imperfect Competition

Table II reports time-series averages of median characteristics of firms sorted on each of the five measures of imperfect product market competition (IPMC): the *HHI* concentration measure (Panel A), the measure of average industry markup (Panel B), the *CBC* measure (Panel C), the *CMC* that combines industry concentration and markup (Panel D), and the *TBC* or text-based measure of competition by Hoberg and Phillips (2010b) (Panel E). Panels A, B, and D cover manufacturing industries, while Panels C and E also cover non-manufacturing industries.

A quick glance at Table II reveals common trends in the statistics across firms sorted on the five measures of IPMC. Book-to-market and earnings-to-price ratios are consistently higher in more competitive industries. These trends are consistent with the hypothesis that less competitive

[21]Given that the distribution of firms' sales is highly skewed, we run our regressions using the logarithm of firms' sales, and then use the definition of the mean and variance of the log normal distribution to compute the adjusted means and variances in levels of sales. See Appendix F

industries have riskier assets. Another common trait of firms in less competitive industries is the more sparing use of financial leverage. A possible explanation for this finding is that capital owners in less competitive firms respond to their greater exposure to risk by reducing financial leverage ratios.

The table shows the median Herfindahl-Hirschman Index based on sales data from Compustat constructed as in Hou and Robinson (2006) across IPMC quintiles. Consistent with the findings in Ali, Klasa, and Yeung (2009), the table shows that there is no clear relation between the Compustat-based concentration measure and measures of IPMC. We argue in this paper that this disconnection is due to sample selection biases of firms that are publicly listed and appear in the Compustat dataset.

The table shows that Novy-Marx's (2011) measure of operating leverage–defined as the ratio of the sum of firms' selling, general and administrative expenses and their costs of goods sold over total assets–is higher in more competitive industries. This trend is consistent with the intuitive implication of Hypothesis 2, all else equal, IPMC leads to higher margins and lower levels of operating leverage.

The table also shows that the median firm market valuation is slightly lower in more competitive industries, although there is no clear trend in median total assets. The table also suggests a negative relation between labor intensity and IPMC, although not consistently across the measures. In particular, Panel A shows no clear relation between labor intensity and *HHI*, possibly due to the fact that the *HHI* measure only covers manufacturing industries and spans a significantly shorter sample period. In what follows, we show that the main predictions of Section I hold after controlling for possible differences in characteristics across firms sorted on IPMC.

<< Table II here >>

III. Empirical Findings

A. Product Market Competition and Scaled Firm Value

Hypothesis 1 predicts that the ratio of assets in place to total firm value is higher in more competitive industries. The corresponding testable implication is that firms in more competitive industries should have higher earnings-to-price ratios and book-to-market ratios, respectively. Table III reports the supporting results for earnings-to-price ratios.

For each measure of competition, we test the link between IPMC and earnings-to-price ratios using two alternative specifications. In the first specification, we simply regress earnings-to-price ratios on the IPMC measure with controls. Given that our dependent variable uses market values, the chosen set of controls does not include dependent variables with market values. Our controls include the capital intensity of the industry and the average firm size as measured by the logarithm of firms' assets.

In the second specification in Table III, we control for the sample selection bias of public listing, and verify the robustness of our results. To adjust earnings-to-price ratios, we regress earnings-to-price ratios on firm-level characteristics and an inverse Mills ratio, which adjusts for the likelihood of observing a public firm. The first-strage results are provided in column XI of Table III. The results of our second stage are reported below each of our measures of IPMC. In the second stage, we regress the residuals of the first stage onto each of our measures of competition.

Consistent with Hypothesis 1, the evidence from the two specifications in Table III shows that earnings-to-price ratios are lower in less competitive industries. Furthermore, we find that private firms have lower earnings-to-price ratios than public firms, given that the coefficient on the inverse Mills' ratio in column IX is significantly positive.

<< Table III here >>

Table IV reports results similar to those in Table III for book-to-market regressions. In the two specifications used, we find that firms in less competitive industries have lower book-to-market ratios on average. This is consistent with the prediction that firms in less competitive industries better preserve the value of their growth options. The results in Table IV also indicate that private firms have significantly higher book-to-market ratios than public firms.

<< Table IV here >>

B. Product Market Competition and Operating Leverage

Hypothesis 2 states that, for the same level of fixed operating costs, the lower profit margins due to product market competition amplify the sensitivity of operating profits to shocks to a firm's productivity (i.e., increases operating leverage). We hereby report empirically that operating leverage is higher in more competitive industries.

As discussed in Section II, we consider two alternative measures of operating leverage. We first run time-series regressions at the industry level of value added growth on total factor productivity growth using NBER/CER data for manufacturing industries. We denote the slope of this regression as $\mathrm{OL}^{\mathrm{TFP}}$. Intuitively, the measure is related to the sensitivity of operating profits to shocks to the industry. In this sense, it captures the level of operating leverage in the industry.

Given the data limitations in the construction of $\mathrm{OL}^{\mathrm{TFP}}$, we also the measure of operating leverage proposed by Novy-Marx (2011) which we here denote $\mathrm{OL}^{\mathrm{Comp}}$.[22] This measure is at the firm level and covers all industries in the Compustat dataset.

Table V shows that, as expected, operating leverage is negatively related to measures of IPMC.

<< Table V here >>

We confirm the negative relation between IPMC and operating leverage in Table VI. We restrict the analysis to the measure of operating leverage from Novy-Marx (2011) $\mathrm{OL}^{\mathrm{Comp}}$ given its longer and broader coverage. We use the two specifications without and with adjustment for sample-correction biases given in regressions (9), (10), and (11). In both cases, we find that firms in more competitive industries have higher operating leverage.

<< Table VI here >>

[22] Here the superscript "Comp" refers to the fact that the measure of operating leverage from Novy-Marx (2011) is based on Compustat data.

C. Product Market Competition and Exposure to Systematic Risk

The third hypothesis of Section I relates to the impact of IPMC on firms' exposure to systematic risk. A challenge for this analysis, and endemic to asset pricing in general, is that expected returns are intrinsically non-observable. We address this problem by considering different sets of tests.

To assess the overall effect of IPMC on firms' exposure to systematic risk, we use proxies for expected returns based on different measures of realized asset returns. Anticipating, we find strong evidence that firms in less competitive industries have higher exposure to systematic risk. This suggests that the investment channel is stronger impact than the operating leverage channel in explaining the relation between IPMC and realized asset returns.

As a last step, we assess the channel through which IPMC affects firms' exposure to systematic risk. For this sake, we assume that the market portfolio captures the source of systematic risk in the economy, which allows us to use market betas as proxies for asset returns. Given this working assumption, we consider the relative contribution of firms' growth options and operating leverage to their risk exposure. Our findings support the insight that the investment channel has a predominant effect in explaining the effect of IPMC on risk exposure.

C.1. Realized Asset Returns

Panel A in Table VII reports that realized asset returns are increasing in the lagged measures of IPMC. The table reports four different measures of asset returns. The first measure is the commonly used excess stock return over the treasury bill rate. To control for the systematic differences across IPMC quintiles suggested in Table II, we also report adjusted stock returns using different specifications. The table shows results of returns adjusted for size, book-to-market, and momentum, according to the methodology in Daniel, Grinblatt, Titman, and Wermers (1997) (*DGTW* returns). To disentangle our risk channel from profitability channel from Novy-Marx (2012), we report results with a variation of *DGTW* returns where we replace momentum for operating margins (EBITDA / Assets) as the third adjusted characteristic.

Table II is consistent with the hypothesis of capital owners responding to higher risk by decreasing leverage ratio. Table VII also supports this hypothesis with results with unlevered returns.

There is no clear consensus in the literature of how to measure unlevered returns. For this reason, we calculate unlevered returns in the simplest possible way: as excess returns times one minus book value of debt over assets minus book value of equity plus market value of equity. Even though unlevered returns are naturally smaller than excess stock returns, unlevered return spreads between firms in less competitive industries and those in more industries are generally more significant than excess stock return spreads.

The adjusted returns employed in the table control for differences in size at the firm level. If firms in less competitive industries are larger than those in more competitive firms, we would still be comparing firms in different size groups in different IPMC portfolios. This raises the concern that results could be simply due to the fact that adjusted returns fail to *fully* control for size differences. To address this concern, Panel B shows the average asset returns of portfolio sorts *within* five sub samples of stocks sorted on size. The panel shows that IPMC is related to higher returns within size groups (i.e., small, medium small, medium, medium large, and large firms).[23]

Table VIII confirms the findings from Table VII in panel data regressions of realized stock returns of firms on the measures of IPMC and firm controls. For each measure of competition, we test the link between IPMC and returns using two alternative specifications. In the first specification we simply regress excess stock returns on the IPMC measure with controls as given by:

$$\mathrm{x}_{j,t,t+1} = \psi_{0,t} + \psi_1 \mathrm{IPMC}_{j,t-1} + \psi_{\mathbf{2,t}} \mathbf{controls_{j,t-1}} + \varepsilon_{\mathbf{j,t}}, \tag{9}$$

where $\mathrm{x}_{j,t,t+1}$ represents the variable of interest and $\psi_{0,t}$ denotes year effects, and $\mathbf{controls_{j,t-1}}$ is a vector of firm-level controls at the end of year $t-1$.[24] The results from this specification are consistent with the predictions of our paper: firm risk, as proxied by realized excess returns, is increasing in IPMC.

Regressions, as opposed to portfolio sorts, allow us to control for sample selection. It is natural to expect systematic differences in riskiness of public and private firms. For instance, if only the safest firms in an industry choose to be publicly listed and if safer industries are more competitive, then one could find a relation between IPMC and firm risk even if there were no direct casual

[23] In unreported results, we find that the return spreads are also robust to forming portfolios within book-to-market groups.

[24] The variable x represents ex post returns in this section. We keep the notation general since we later refer to this specification for alternative left-hand side variables.

relation. From this insight, we run a specification in two stages. To adjust returns, we regress stock returns on firm-level characteristics and an inverse Mills ratio, which accounts for the sample selection bias of public listing. We consider the same firm-level controls as in Equation (9) such that [25]

$$x_{j,t,t+1} = \psi^1_{0,t} + \psi^1_1 \lambda_{j,t-1} + \boldsymbol{\psi^1_{2,t}} \mathbf{controls_{j,t-1}} + \boldsymbol{\varepsilon^1_{j,t}}, \tag{10}$$

where λ is the inverse Mills ratio. Since this regression is the same for all our measures of competition, we report its results in the last column of Table VIII. We then regress the adjusted returns on each of the measures of IPMC:

$$\varepsilon^1_{j,t} = \psi^2_0 + \psi^2_1 \text{IPMC}_{j,t-1} + \varepsilon^2_{j,t}. \tag{11}$$

The empirical evidence in Table VIII on this alternative specification shows that firms in more competitive industries are less risky. The empirical results of the regression labeled as column IX in Table VIII indicate that public firms earn lower returns than private firms.

<< *Table VIII here* >>

C.2. Loadings on Market Risk

Realized stock returns are noisy proxies for expected returns, which is particularly problematic given the relatively short sample period of financial data commonly used in the literature. It is a well-known fact that estimates of betas are more precise than those of average returns. Our hypotheses in Section I are agnostic on the identity of the single source of systematic risk in the economy. In order to use betas, we make in this section the additional assumption that the market portfolio contains a significant portion of the economy's systematic risk. This assumption implies that firms with higher loadings on the market portfolios (i.e., with high CAPM market betas) should earn higher returns in expectation.

We allow betas to change over time and construct conditional betas. Betas are constructed as in Lewellen and Nagel (2006) and defined as the slope of univariate 12 month rolling regressions of excess returns on the market portfolio one year ahead. We also construct unlevered betas calculated

[25] For the sake of brevity, we provide the details on the construction of the inverse Mills' ratio to Appendix F.

as market betas times one minus lagged leverage ratio. Unlevered betas are used for the same reason that we also use unlevered returns in the previous section: to also consider the possibility that results are partially offset by the owners of capital in their capital structure decisions. Table IX reports that betas, and in particular unlevered betas, are increasing in the IPMC measures. Panel A of the table reports results of standard sorts, while Panel B reports results of sorts within size quintiles. Hypothesiss are more significant when we control for differences in firm size across industries.

<< Table IX here >>

We confirm the results from Table IX using regressions. We employ the same two specifications used in Table VIII given in regressions (9), (10), and (11), where the variable or interest (i.e., x) is conditional beta. In the first specification we regress conditional betas on the IPMC measure and firm level-controls. In the second specification, we used a two-pass methodology similar where we adjust returns for the sample selection bias of public listing. The evidence shows that conditional betas are increasing in the measures of IPMC. This relation is not explained by other firm characteristics also related to betas, such as size and the book-to-market ratio. Similarly, we find that firms' betas adjusted for firm-level controls and the inverse Mills' ratio are also higher in less competitive industries. Consistent with our findings in Table VIII, the evidence in column IX of Table X indicates that the betas of public firms are significantly lower than the betas of private firms.

<< Table X here >>

Our hypothesis is that the lower riskiness of firms in more competitive industries arises from the impact of product market competition on their growth options, despite their greater operating leverage. To test this hypothesis, we apply our derivation in Section I and decompose unlevered betas into revenue, growth, and operating cost betas. The decomposition is given by:

$$\beta^{\mathrm{UN}} = \underbrace{\mathrm{BM}\,\beta^{\mathrm{R}}}_{\text{revenues}} + \underbrace{(1-\mathrm{BM})\,\beta^{\mathrm{G}}}_{\text{growth options}} + \underbrace{\mathrm{BM}\,\mathrm{OL}\,\beta^{\mathrm{R}}}_{\text{operating leverage}} \tag{12}$$

We first apply the methodology by Bernardo, Chowdhry, and Goyal (2007) to decompose betas into the asset component and the growth option component. This methodology is based on the assumption that asset betas and growth betas are constant within industry firms in a given year.[26] We then decompose the asset component into the revenues and operating leverage component. For the second decomposition, we use the measure of operating leverage from Novy-Marx (2011) (the sum of cost of good sales and sales, COGS, and general, and administrative expenses, XSGA, over revenues).[27]

Panel A of Table XI reports the average estimated revenue and growth beta, β_i^R and β_i^G, across IPMC portfolios. The table shows that the extra riskiness of firms in less competitive industries is attributed to both the extra riskiness of revenues and growth options.

Panel B of Table XI reports the weights of the operating leverage and growth option components of (12) across IPMC portfolios. The table shows that, in general, the operating leverage component is larger for more competitive industries, and the growth option component is larger for less competitive industries.

<< Table XI here >>

Put together, the results of Tables V, VI and XI show that the intuition that firms with lower operating margins have with higher exposure to risk does not always hold. It is worth noting that operating leverage should *increase* firm risk in a way similar to financial leverage. While it is true that firms in more competitive industries have higher operating leverage, firms' risk exposure is lower–not higher–in more competitive industries. In this sense, the fact that firms in more competitive industries have higher levels of operating leverage makes the evidence that asset returns are increasing in IPMC even more remarkable.

IV. Conclusion

In this paper we provide empirical evidence that product market competition has an economically significant effect on average industry returns, and that this effect is consistent with the predictions of previous theoretical contributions. In our empirical tests, we show that product market

[26]Please see Bernardo, Chowdhry, and Goyal (2007) for details about the methodology.

[27]The measures of BM and OL are used as linear approximations for the true weights of assets and operating leverage on total firm value, respectively. We experimented multiplying (separately) the OL and BM measures by different constants (ranging from 1/2 to 2) without big effect on our findings.

competition has two opposing effects on a firm's exposure to systematic risk. The first effect is that product market competition reduces the value of growth options which in turns reduces loadings on systematic risk. The intuition for this effect is that the value destruction due to threat of entry or expansion by competitors is pro-cyclical, which effectively reduces firm risk. The second effect is that, unconditionally, competition erodes the value of the firm by reducing operating profits, which effectively increases operating leverage and exposure to systematic risk.

We find that the first effect generally dominates so that firms in less competitive industries earn higher returns. Moreover, we report that firms in competitive industries have higher earnings to price ratios and higher book to market ratios. This is consistent with the intuition that firms in less competitive industries better preserve the value of their growth options. We document that firms in more competitive industries have higher operating leverage. Lastly, our empirical approach allows us to infer that private firms earn on average higher returns, and that they have lower earnings-to-price ratios and lower book-to-market ratios than publicly listed firms.

To assess the impact of product market competition on firm value and exposure to risk, we use multiple measures of imperfect product market competition. Two of these measures are based on U.S. Census data and are restricted to manufacturing industries. To expand our analysis to non-manufacturing industries, we construct an additional measure of industry concentration. Our measure is available for all industry-years in the Compustat dataset. We consider a measure that integrates markup and concentration and a measure solely based on 10K information as robustness checks. We also verify the robustness of our results by controlling for the sample selection bias of public listing.

The empirical findings of our paper emphasize the importance of the competitive environment in explaining the cross section of returns. For instance, the common assumptions that firms operate in either monopolies or under perfect competition need not be innocuous in theoretical asset pricing models. Our paper also highlights the importance of correcting for the sample selection bias of the returns of publicly listed firms. We argue that this correction may be significant for empirical studies that link asset returns to any industry characteristic.

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Appendix

A. A parsimonious real options model

We first specify the set-up which allows us to prove formally each of our predictions in Section I. We provide the formal proofs of each of these predictions in subsequent appendices. We follow Berk, Green, and Naik (1999) and take the pricing kernel as exogenous. The dynamics of the pricing kernel Λ are given by:

$$d\Lambda_t = -r\Lambda_t dt - \eta\Lambda_t dz_t, \tag{A1}$$

where dz is a Wiener processes that represents the single source of systematic risk, $r > 0$ is the instantaneous risk-free rate, and $\eta > 0$ is the market price of risk in the economy.

We consider an industry composed of a $N \geq 1$ firms indexed by j with identical productive technologies. In what follows, we use lower case letters for firm-level variables and upper case letters for industry- or economy-level ones. To save on notation, we omit the firm subscript j from lower case variables unless it is strictly necessary. Output at the firm level is given by:

$$y_t = A_t k_t^{\alpha} l_t^{1-\alpha}, \tag{A2}$$

where l is the number of labor hours and k is the amount of capital employed in production, $0 < \alpha < 1$ is the capital intensity, and $A > 0$ is the industry's total factor productivity (TFP). TFP A follows a diffusion process given by:

$$dA_t = \mu_{\mathrm{A}} A_t dt + \sigma_{\mathrm{A}} A_t dz_t. \tag{A3}$$

The industry produces and sells a single homogeneous good subject to a downward sloping demand curve. The price of the good is given by:

$$P_t = Y_t^{-\frac{1}{\varepsilon}}, \tag{A4}$$

where $\varepsilon > 1$ is the elasticity of demand, and $Y \equiv \sum_{j \leq N} y_j$ is the total industry output.

Firms produce one unit of the final product sold in the industry by combining irreversible capital k_t and a fully reversible input of production, which we label for simplicity as labor or l_t. We assume that firms produce at full capacity. We further assume perfect competition in labor markets and full mobility of workers across industries such that, regardless of the level of competition, firms take wages w as given.

To study the impact of operating leverage on firm risk, we assume that firms have fixed operating costs fk_t which are unrelated to productivity but proportional to the firm's scale. The introduction of fixed operating costs implies that the firm is subject to operating losses.

Firms' operating profits are defined as revenues net of wages times the level of employment. Firms optimize profits by determining the optimal amount of labour each period. Optimized operating profits, π, are given by:

$$\pi_t \equiv \max_{l_t} \left(P_t A_t k_t^{\alpha} (l_t)^{1-\alpha} - w l_t - f k_t \right). \tag{A5}$$

Firms can also incrementally and irreversibly adjust capital by increasing installed capacity by $dk_t \geq 0$ at a marginal cost $\kappa_P > 0$.[28] The owners of capital receive a dividend stream that equals operating profits net of investment costs, $\pi_t dt - dk_t \kappa_P$.

A.1. General Solution for Firm Value

We follow the literature and assume that productivity shocks can be perfectly replicated with tradable securities.[29] The value of a firm, V_t, is defined as the maximized expected discounted stream of dividends that belong to the owners of capital:

$$V_t \equiv \max_{\{dk_s\}_{s \geq t}} \left(\mathrm{E}_t \left[\int_t^{\infty} \frac{\Lambda_s}{\Lambda_t} (\pi_s ds - \kappa_P dk_s) \right] \right). \tag{A6}$$

For sake of tractability in what follows, we denote by Π_t/δ the net present value of the assets in place for the firm, namely

$$\frac{\Pi_t}{\delta} \equiv \frac{\hat{\pi}_t}{\delta} - \frac{f k_t}{r}. \tag{A7}$$

where $\hat{\pi}_t \equiv \pi_t + f k_t$ the the optimized variable profits of the firm before fixed operating costs, and $\delta > 0$ is the risk-and-growth-adjusted discount rate. The constant $\delta > 0$ is provided in Appendix A.4. The first term $\hat{\pi}_t/\delta$ equals the present value of the discounted stream of variable operating profits generated by the firm's current assets. The second component is the present value of the fixed costs of the firm at its current scale, which is discounted at the risk free rate since the magnitude of fixed costs does not vary stochastically.

Using standard techniques, it is straightforward to show that V_t contains three main components, namely:

$$V_t = \frac{\Pi_t}{\delta} + G_+ X_t^{\upsilon_G} - G_- X_t^{\upsilon_G}, \tag{A8}$$

where the subscript $+$ denotes expected changes in the value of the firm due to its own investment decisions, the subscript $-$ denotes the expected changes in the value of the firm due to the investments of its competitors, $X_t \equiv A_t^{\varepsilon-1}$, and the $\upsilon_G > 1$, G_+, and G_- are positive constants.

The first component of the value of the firm in equation (A8) reflect the value of the assets in place of the firm. The second component, $G_+ X_t^{\upsilon_G}$, is related to the present value of the discounted cash flows generated by future additions in the installed capacity of the firm. The last component, $-G_- X_t^{\upsilon_G}$, accounts for expected changes in the value of the firm caused by additions to industry capacity by competing firms. Equation (A8) shows that the value of a firm

[28] The subscript P refers to the cost of increasing capital, κ_P, being equivalent to a purchase price per unit of capital.

[29] Examples of this literature are Berk, Green, and Naik (1999), Goldstein, Ju, and Leland (2001), and Carlson, Fisher, and Giammarino (2004).

depends on all investment opportunities in the industry, both the ones held by the firm and also its competitors.

A.2. General Solution for Expected Asset Returns

Expected asset returns are defined as the drift of the gains process that reinvests dividends into a tradable asset that perfectly replicates the value of the firm. From equation (A8), we have that:

$$\begin{aligned} \mathrm{E_t}[R_t] &\equiv \mathrm{E_t}\left[\frac{dV_t + \pi_t dt - \kappa_{\mathrm{P}} dk}{V_t}\right] \\ &= r + \beta_t \eta, \end{aligned} \tag{A9}$$

where β is the firm asset value returns' loading on the single source of priced risk in the economy and is given by:

$$\beta_t = \frac{\Pi_t/\delta}{V_t}\sigma_{\mathrm{X}}\gamma + \left(1 - \frac{\Pi_t/\delta}{V_t}\right)\sigma_{\mathrm{X}}\upsilon_{\mathrm{G}} + \frac{fk_t/r}{V_t}\sigma_{\mathrm{X}}\gamma, \tag{A10}$$

where σ_{X} is the volatility of the scaled TFP shock, X_t, and $0 < \gamma \equiv (1-\alpha)(1-\frac{1}{\varepsilon}) < 1$.

Equation (A10) characterizes the exposure to systematic risk of the firm as the weighted portfolio of the riskiness of its variable operating profits, the riskiness of the growth opportunities of the industry, and the riskiness due to its fixed operating costs. The first term of equation (A10) shows that the fundamental beta of firms' variable operating profits is given by $\sigma_{\mathrm{X}}\gamma$. The second term of (A10) shows that the beta of the portfolio of the future expected changes to the assets in place from the firm and its competitors equals $\sigma_{\mathrm{X}}\upsilon_G$. The third term indicates that firms' fixed operating costs contribute to their exposure to risk.

An important insight of Equation (A10) is that the positive root of the fundamental quadratic υ_{G} captures the riskiness of the growth opportunities of the industry. For any type of industry, the riskiness of growth options is higher than that of assets in place since $\gamma < 1 < \upsilon_G$. In our model, firms' future investment opportunities are levered positions in assets that have the same riskiness of assets in place.

A.3. Product Markets

The degree of product market competition is determined by the significance of the interactions between firms in the industry. To capture this intuition, we focus on the two extreme cases of product market competition: no competition (monopoly) and perfect competition. We show that these two extreme cases illustrate how competition affects a firm's value and exposure to systematic risk.[30]

In the monopolist case, $N = 1$, the single firm in the industry is insulated by high barriers to entry and is thus

[30] Although not explicitly modeled here, related literature suggests that the case with imperfect product market competition combines elements of the two extreme cases discussed here. Examples of this are the studies by Dockner, Carlson, Fisher, and Giammarino (2011) and Bustamante (2012), who consider asset pricing models of strategic investment in oligopolistic industries.

unaffected by other firms' decisions.[31] In the perfect competition case, $N \gg 1$ and the industry has no barriers for new entrants. Any given firm in the industry is unable to directly affect other firms, current competitors or potential entrants, while it is greatly affected by their joint decisions.

We compare the two types of industries at a point in time where the aggregate amount of capital in each industry is the same and equal to K:

$$K_t^{\mathrm{M}} = K_t^{\mathrm{C}} \equiv \sum_{j=1}^{N} k_t = K_t, \tag{A11}$$

where the superscripts M and C denote the monopolist and competitive cases, respectively.

A.4. Model Solution for Monopoly

The free cashflows of the firm are given by $\pi^{\mathrm{M}} - \kappa_{\mathrm{P}} dK$. Solving for the optimal labor decision of the firm, we get the alternative expression for the operating profits:

$$\pi_t^{\mathrm{M}} = \Gamma^{\mathrm{M}} X_t^{\gamma} K^{1-\gamma} - fK,$$

where Γ^{M} is given by:

$$\Gamma^{\mathrm{M}} = \frac{(1+\alpha(\varepsilon-1))}{\varepsilon} \left(\frac{\gamma}{w}\right)^{\gamma(1-\alpha)(\varepsilon-1)}.$$

V^{M} is a function of the capital stock K and the stochastic variable X. Using the same argument as in Abel and Eberly (1996), we note that the functions π^{M} and V^{M} are homogeneous of degree one, such that:

$$V_t^{\mathrm{M}}(K,X) = K_t v^{\mathrm{M}}\left(\frac{X_t}{K_t}\right) \quad \text{and}$$
$$\pi_t^{\mathrm{M}}(K,X) = K_t \pi^{\mathrm{M}}\left(\frac{X_t}{K_t}\right).$$

We denote the ratio $\frac{X}{K}$ by x and the optimal value of x at which the monopolist invests by x^{M}. The problem of the monopolist is to maximize the ODE of v_t^{M}, namely:

$$rv = \pi^{\mathrm{M}} + x\mu_x v^{\mathrm{M}} + (\mu_x - \eta\sigma_x) x v^{\mathrm{M}\prime} + \frac{1}{2}\sigma_x^2 x^2 v^{\mathrm{M}\prime\prime}. \tag{A1}$$

We conjecture that v_t^{M} has the functional form given by:

$$v_t^{\mathrm{M}} = \frac{\Gamma^{\mathrm{M}}}{\delta} x_t^{\gamma} - \frac{f}{r} + G^{\mathrm{M}} x_t^{\upsilon_{\mathrm{M}}} + D^{\mathrm{M}} x_t^{\upsilon_{\mathrm{D}}}, \tag{A2}$$

[31] Examples of barriers to entry include government regulation, intellectual property rights, high irreversible investment costs, and predatory pricing, among others.

where the constant δ is defined for convenience to ease on notation, such that

$$\delta = r - \gamma\left[\mu_x - \sigma_x\eta - \frac{1+\gamma(\varepsilon-1)}{2(\varepsilon-1)^2}\sigma_x^2\right] > 0,$$

the constants $\upsilon_{\text{G}} > 1$ and $\upsilon_{\text{D}} < 0$ are, respectively, the positive and negative roots of the fundamental quadratic, such that:

$$\upsilon_{\text{G}} = \frac{1}{2} - \frac{(r-\delta)}{\sigma_x} + \left(\left(\frac{(r-\delta)}{\sigma_x}\right)^2 + 2\frac{\mu_x}{\sigma}\right)^{0.5} > 1 \quad \text{and}$$
$$\upsilon_{\text{D}} = \frac{1}{2} - \frac{(r-\delta)}{\sigma_x} - \left(\left(\frac{(r-\delta)}{\sigma_x}\right)^2 + 2\frac{\mu_x}{\sigma}\right)^{0.5} < 0,$$

and G^{M} and D^{M} are constants to be determined.

The region of zero investment of the monopolist includes the limit as x goes to zero. To keep v^{M} finite, we leave the negative power of x out of the solution, and set $D^{\text{M}} = 0$. The remaining constant G^{M} is determined by considering the optimal investment decision of the firm. We impose the optimality condition that the marginal product of capital equals the marginal cost κ_{P}, namely:

$$v^{\text{M}}(x) - xv^{\text{M}\prime}(x) = \kappa_{\text{P}}.$$

The other requirement for the optimality of investment is that the derivative with respect to x of the condition above equals zero, namely:

$$\frac{\partial(v^{\text{M}}(x) - xv^{\text{M}\prime}(x))}{\partial x_t} = 0.$$

These equations provide a system with two unknowns, where the unknowns are G^{M} and x^{M}. The solution for G^{M}:

$$G^{\text{M}} = G^{\text{M}}_{+} = \frac{\gamma\left(\kappa_{\text{P}} + \frac{f}{r}\right)}{(\upsilon_{\text{G}}-\gamma)(\upsilon_{\text{G}}-1)}\left[\frac{\Gamma^{\text{M}}(1-\gamma)(\upsilon_{\text{G}}-\gamma)}{\delta\left(\kappa_{\text{P}} + \frac{f}{r}\right)\upsilon_{\text{G}}}\right]^{\frac{\upsilon_{\text{G}}}{\gamma}} > 0. \tag{A3}$$

For the sake of generality, the constant G^{M} in Section I uses a slightly different notation, such that it is equal to the product of the equation above times $K^{1-\upsilon_G}$.

The optimal investment threshold x^{M} that solves the equations above is:

$$x^{\text{M}} = \left[\frac{\Gamma^{\text{M}}}{\delta}\frac{(1-\gamma)(\upsilon_{\text{G}}-\gamma)}{\left(\kappa_{\text{P}} + \frac{f}{r}\right)\upsilon_{\text{G}}}\right]^{-\frac{1}{\gamma}}.$$

A.5. Model Solution for Perfect Competition

Our derivation follows Leahy (1993). Solving for the optimal labor decision of the firm, we get the alternative expression for the operating profits:

$$\pi_t^{\mathrm{C}} = \Gamma^{\mathrm{C}} X_t^{\gamma} K_t^{-\gamma} - fk,$$

where N is the total number of firms in the industry, each the firm has k units of capital, and Γ^{C} is given by:

$$\Gamma^{\mathrm{C}} = \left(\frac{1-\alpha}{w}\right)^{(1-\alpha)(\varepsilon-1)\gamma} k. \tag{A1}$$

We denote the ratio $\frac{X}{K}$ by x and the optimal entry threshold by x^{C}. The value and profits of the firm are homogeneous of degree zero in X and K, so we solve for the value of the firm as a function of x. The ODE of the value of the incumbent firm V_j^{C} is given by:

$$rV_j^{\mathrm{C}} = \pi^{\mathrm{C}} + x\mu_x V_j^{\mathrm{C}} + (\mu_x - \eta\sigma_x)xV_j^{\mathrm{C}\prime} + \frac{1}{2}\sigma_x^2 x^2 V_j^{\mathrm{C}\prime\prime}. \tag{A2}$$

We conjecture that the value of the incumbent firm V_j^{C} has the functional form given by:

$$V_t^{\mathrm{C}} = \frac{\Gamma^{\mathrm{C}}}{\delta} x_t^{\gamma} - \frac{fk}{r} + G^{\mathrm{C}} x_t^{\upsilon_{\mathrm{G}}} + D^{\mathrm{C}} x_t^{\upsilon_{\mathrm{D}}}, \tag{A3}$$

where $\upsilon_{\mathrm{G}} > 1$ and $\upsilon_{\mathrm{D}} < 0$ are, respectively, the positive and negative roots of the fundamental quadratic, and G^{C} and D^{C} are constants to be determined.

To keep V_j^{C} finite, we leave the negative power of x out of the solution, and set $D^{\mathrm{C}} = 0$. The remaining constant G^{C} is determined by considering the optimal investment decision of the new entrants. We define the value of any new entrant by V_{-}^{C} and conjecture that:

$$V_{-t}^{\mathrm{C}} = E^{\mathrm{C}}(x_t)^{\upsilon_{\mathrm{G}}}.$$

The unknowns are therefore G^{C}, E^{C}, and the entry threshold x^{C}. We first impose the optimality condition that the value of the new entrant net of the investment cost equals the value of the incumbent, namely:

$$V_t^{\mathrm{C}}(x) = V_{-jt}^{\mathrm{C}}(x) - \kappa_{\mathrm{P}} k.$$

Another requirement is given by the smooth pasting condition:

$$\frac{\partial V_t^{\mathrm{C}}(x)}{\partial x_t} = \frac{\partial V_{-jt}^{\mathrm{C}}(x)}{\partial x_t}.$$

Finally, we require that the derivative of V_t^{C} with respect to X is zero, namely:

$$\frac{\partial V_t^{\mathrm{C}}(x)}{\partial x_t} = 0.$$

The conditions above imply that E^{C} equals zero: the option value of an idle firm is zero under perfect competition.

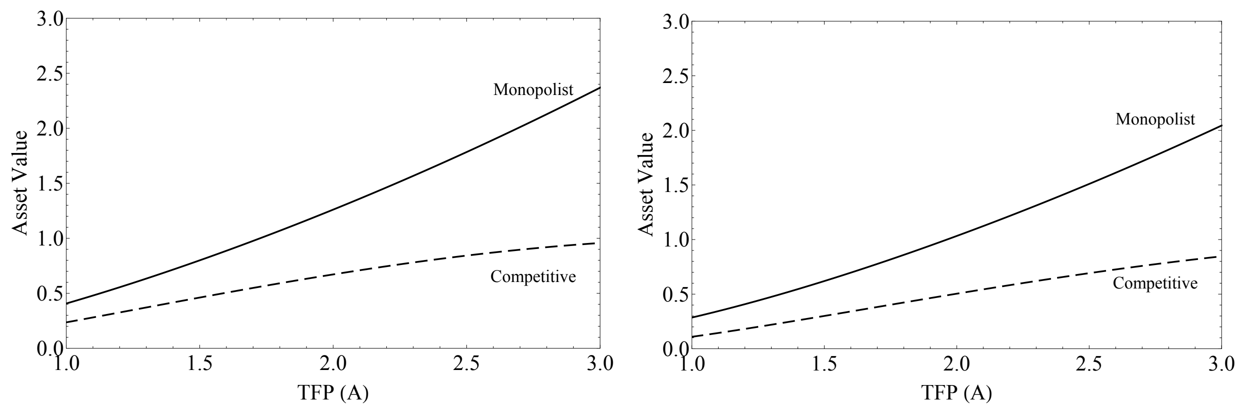
The solution for G^{C} is:

$$G^{C} = -G^{C}_{-} = -\frac{\gamma\Gamma^{C}}{\upsilon_{G}}\left[\frac{\Gamma^{C}(\upsilon_{G}-\gamma)}{\left(\kappa_{P}+\frac{f}{r}\right)\upsilon_{G}k}\right]^{\frac{\upsilon_{G}}{\gamma}-1} < 0.$$

For the sake of generality, the constant G^{C} in Section I uses a slightly different notation, such that it is equal to the product of the equation above times $K^{-\upsilon_G}$. Finally, the optimal investment threshold x equals:

$$x^{C} = \left[\frac{\Gamma^{C}}{\delta}\frac{(\upsilon_{G}-\gamma)}{\left(\kappa_{P}+\frac{f}{r}\right)\upsilon_{G}k}\right]^{-\frac{1}{\gamma}}.$$

Figure A1 below shows the values of the firm for the cases of perfect competition and monopoly, for the cases with low (Panel A) and high (Panel B) fixed operating costs. The figure illustrates that product market competition unconditionally destroys firm value. Moreover, the figure shows that the value destruction is procyclical, i.e., is larger when productivity is larger.



(a) Panel A: Low Fixed Operating Costs

(b) Panel B: High Fixed Operating Costs

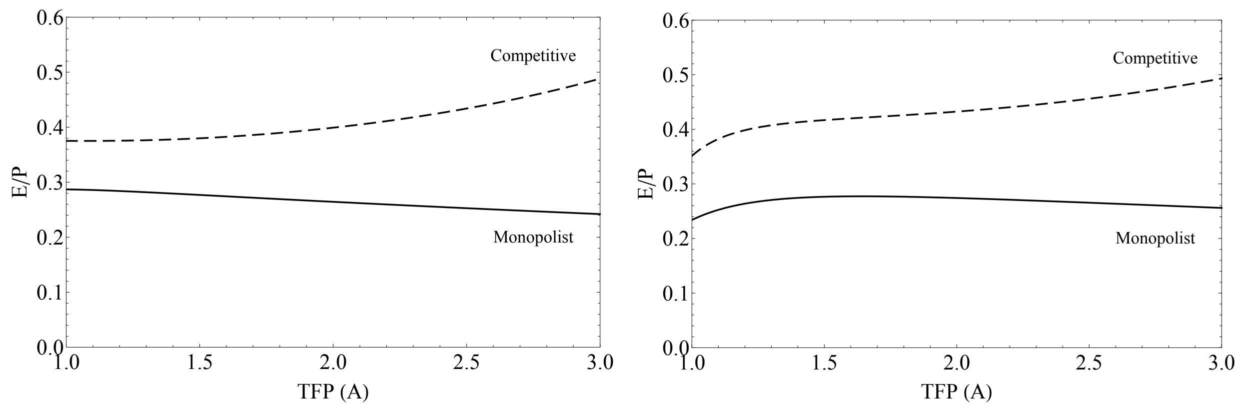
Figure A1. Model solution: Firm value for different levels of industry total factor productivity. Parameters values used in plots: $\varepsilon = 3$, $\eta = 0.4$, $r = 5\%$, $w = 2$, $\alpha = 0.33$, $\mu_{A} = 0\%$, $\sigma_{A} = 50\%$, $K = 1$, $N = 1$, and $\kappa_{P} = 1$, $f = 0.05$ (Panel A), and $f = 0.10$ (Panel B).

B. Hypothesis 1

The ratio of assets in place over total value is lower in firms in less competitive industries, than in otherwise identical firms in more competitive industries, such that

$$\frac{\Pi_t^{\mathrm{M}}/\delta}{V_t^{\mathrm{M}}} < \frac{\Pi_t^{\mathrm{C}}/\delta}{V_t^{\mathrm{C}}}. \tag{B4}$$

The inequality relies on the fact that $G^{\mathrm{M}} > 0$ while $G^{\mathrm{C}} < 0$. From these inequalities, we get that $\frac{\hat{\pi}_t^{\mathrm{M}}/\delta - fK_t/r}{V_t^{\mathrm{M}}} < 1$ while $\frac{\hat{\pi}_t^{\mathrm{C}}/\delta - fk_t/r}{V_t^{\mathrm{C}}} > 1$. Hence $\frac{\hat{\pi}_t^{\mathrm{M}}/\delta - fK_t/r}{V_t^{\mathrm{M}}} < \frac{\hat{\pi}_t^{\mathrm{C}}/\delta - fk_t/r}{V_t^{\mathrm{C}}}$. This result is illustrated in Figure B2. The figure illustrates that, all else equal, firms in more competitive industries have higher earnings-to-price ratios.



(a) Panel A: Low Fixed Operating Costs

(b) Panel B: High Fixed Operating Costs

Figure B2. Model solution: Earnings-to-price ratio for different levels of industry total factor productivity. Parameters values used in plots: $\varepsilon = 3$, $\eta = 0.4$, $r = 5\%$, $w = 2$, $\alpha = 0.33$, $\mu_{\mathrm{A}} = 0\%$, $\sigma_{\mathrm{A}} = 50\%$, $K = 1$, $N = 1$, and $\kappa_{\mathrm{P}} = 1$, $f = 0.05$ (Panel A), and $f = 0.10$ (Panel B).

C. Hypothesis 2

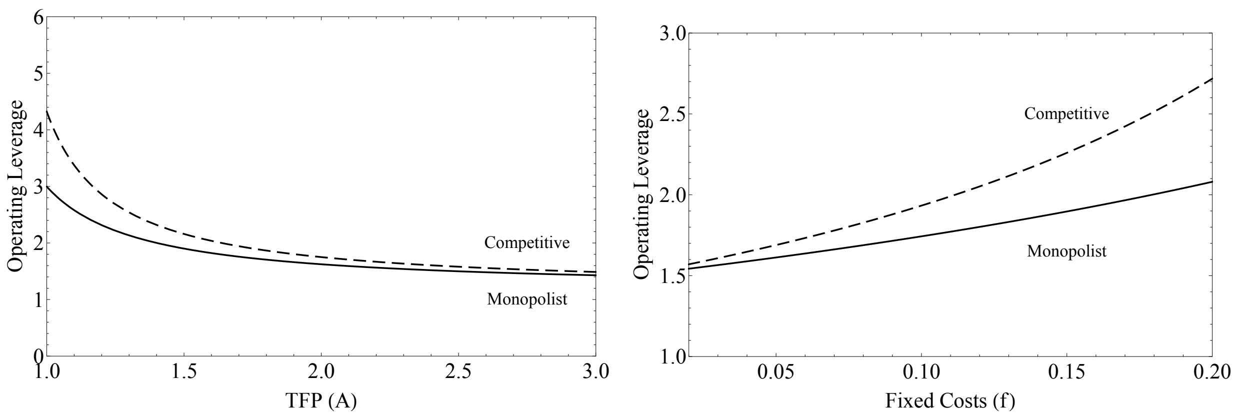
The model characterizes how firms' fixed costs of production affect their operating leverage under different industry structures. We define operating leverage as the degree of sensitivity of operating profits to productivity shocks, such that:

$$\Theta \equiv \mathrm{Cov}\left[\frac{d\pi}{\pi}, \frac{dA}{A}\right] \Big/ \mathrm{Var}\left[\frac{dA}{A}\right] - 1, \tag{C1}$$

and we show in our simple model that the operating leverage of the firm is mechanically increasing in its fixed costs of production for any type of industry. The model predicts that, for a given level of fixed costs per unit of capital f, firms' operating leverage is higher in firms in more competitive industries. All else being the same, the degree of operating leverage of a competitive firm is greater than that of a monopolistic one, such that

$$\Theta_t^{\mathrm{M}} = \gamma(\varepsilon-1)\left(\frac{fk_t}{\pi_t^{\mathrm{M}}}+1\right) < \Theta^{\mathrm{C}} = \gamma(\varepsilon-1)\left(\frac{fk_t}{\pi_t^{\mathrm{C}}}+1\right). \tag{C2}$$

The inequality follows from on the fact that, all else equal, $\frac{\pi^{\mathrm{C}}}{k} > \frac{\pi^{\mathrm{M}}}{K_t}$. In particular, total capital in both industries is equal to K_t. It follows that $\Gamma^{\mathrm{C}} < \Gamma^{\mathrm{M}}$. This result shows that a firm in a less competitive industry earns higher operating margins that partially buffer negative shocks. Figure C3 illustrates that operating leverage is unconditionally higher in more competitive industries.



(a) Panel A: TFP

(b) Panel B: Fixed Operating Costs

Figure C3. Model solution: Operating Leverage for different levels of TFP and fixed operating costs. Parameters values used in plots: $\varepsilon = 3$, $\eta = 0.4$, $r = 5\%$, $w = 2$, $\mu_{\mathrm{A}} = 0\%$, $\sigma_{\mathrm{A}} = 50\%$, $K = 1$, $N = 1$, and $\kappa_{\mathrm{P}} = 1$. Additional parameter values used: $f = 0.1$ (Panel A) and $A = 4$ (Panel B).

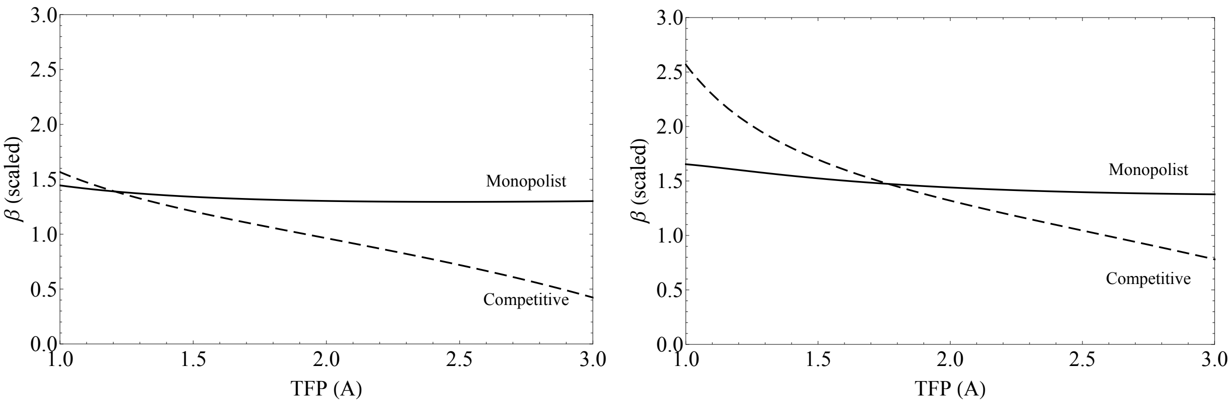
D. Hypothesis 3

All else being the same, the difference in betas between of a monopolistic firm and a competitive firm is such that

$$\beta_t^{\mathrm{M}} - \beta_t^{\mathrm{C}} \equiv (\sigma_{\mathrm{X}}\gamma - \sigma_{\mathrm{X}}\upsilon_{\mathrm{G}})\left(\frac{\Pi_t^{\mathrm{M}}/\delta}{V_t^{\mathrm{M}}} - \frac{\Pi_t^{\mathrm{C}}/\delta}{V_t^{\mathrm{C}}}\right) + \sigma_{\mathrm{X}}\gamma\left(\frac{fK_t/r}{V_t^{\mathrm{M}}} - \frac{fk_t/r}{V_t^{\mathrm{C}}}\right), \tag{D1}$$

The first term in the definition above is strictly positive. To see this, note that the first factor in the first term is strictly positive since $\gamma < 1$ and $\upsilon_{\mathrm{G}} > 1$. The second factor in the first term is strictly positive given our derivation in Appendix B. The second term is strictly negative. To see this, note that the first factor is strictly positive. The second factor is strictly negative since $\frac{fK_t}{rV_t^{\mathrm{M}}} < \frac{fk_t}{rV_t^{\mathrm{C}}}$. This is illustrated by comparing Panels A and B in Figure D4. When fixed costs are relatively small (Panel A), the investment channel is stronger.

The result that product market competition may either reduce or increase risk exposure as shown in Figure D4 is consistent with the model proposed by Aguerrevere (2009). Aguerrevere (2009) considers a model of oligopoly in which firms are subject to fixed costs of production, and shows that product market competition affects expected returns differently depending on the level of market demand. For high levels of productivity, the relation between product market competition and risk exposure is positive, i.e. the investment channel prevails.



(a) Panel A: Low Fixed Operating Costs

(b) Panel B: High Fixed Operating Costs

Figure D4. Model solution: Asset beta for different levels of industry total factor productivity. Parameters values used in plots: $\varepsilon = 3$, $\eta = 0.4$, $r = 5\%$, $w = 2$, $\alpha = 0.33$, $\mu_A = 0\%$, $\sigma_A = 50\%$, $K = 1$, $N = 1$, and $\kappa_P = 1$, $f = 0.05$ (Panel A), and $f = 0.10$ (Panel B).

E. Database Construction

Monthly common stock and accounting data are from firms covered in the CRSP/Compustat merged files that are listed on NYSE, AMEX, and NASDAQ. We follow the literature and exclude regulated (SIC codes between 4900 and 4999) and financial firms (SIC codes between 6000 and 6999). We exclude firm-year observations with at least one missing monthly return observation in the year or with a missing size, book-to-market, or leverage observation in the previous year. Firm-level accounting variables and size measures are Winsorized at the 0.5% level in each sample year to reduce the influence of possible outliers. For the same reason, we exclude from the sample the bottom 5^{th} size percentile of the sample of firms to avoid anomalies driven by micro-cap firms, as discussed by Fama and French (2008).

Size is defined as the market value of equity. Book value is defined as shareholders' equity (Compustat SEQ) divided by the market value of equity. We require the measures of book-to-market and size to be available at least seven months prior to the test year. Leverage ratios are calculated as the book value of debt adjusted for cash holdings, as reported in Compustat, divided by the sum of market value of equity and book value of debt (market-valued leverage ratio). Labor intensity is defined as the ratio of employment compensation divided by the industry value added net of taxes and subsidies, based on the U.S. Industry Account Dataset published by BEA.

To compute the conditional betas that we use in our empirical tests, we first estimate pre-ranking betas on 60 monthly returns for individual stocks. We form 100 portfolios of stocks each year, double sorted on 10 lagged size groups and 10 lagged pre-ranking market beta groups. Size groups are defined by NYSE-based breakpoints to prevent overweighting very small stocks. We then estimate betas for each of the portfolios using the full sample period and assign the respective beta to each stock in the portfolio in each year. Market betas are robust for non-synchronous stock return data and are constructed, as in Dimson (1979), as the sum of the slope coefficients of regressions of excess returns on contemporaneous and lagged market excess returns.

We also construct variables to use as controls in the first stage of the construction of the CBC measure discussed in Appendix . The industry growth in sales and the the volatility in the industry growth is constructed using the item sale in Compustat. The share of firms in the industry with positive expenses in RD is constructed using the item xrd in Compustat; the share of firms with positive dividends in the industry is constructed using the item div in Compustat. The share of firms with zero financial debt in the industry is constructed using the item dltt in Compustat.

F. Correction for Sample Selection Bias and CBC measure

We correct for the sample selection bias of publicly listed firms in two stages. First, we compute inverse Mills' ratios by industry-year to control for the probability that a firm is public in the working sample. Second, we use these ratios to either correct average industry characteristics for sample selection bias or as a regressor in our panel regressions.

Let there be $N_{it}^{\mathcal{C}}$ public firms that are tracked by Compustat and $N_{it}^{\mathcal{P}}$ private firms in industry i in year t. Let h_{jit} denote an observable characteristic (i.e., the sales of a Compustat firm j in industry i at year t). This datum can be decomposed as:

$$h_{jit} = \psi_t \mathbf{x_{it}} + \varepsilon_{\mathbf{jt}},$$

where $\psi_t \mathbf{x_{it}}$ is the true population mean in that industry-year, $\mathbf{x_{it}}$ is a vector of industry-specific variables, and ε_{jt} is the firm-specific deviation from the mean, such that $E(\varepsilon_{jt}) = 0$ and errors are heteroskedastic, such that $Var(h_{it}) = Var(\varepsilon_{jt}) \equiv \sigma_i^2$. If ε is correlated with one of the reasons why the firm is public, then our estimation is biased.

We compute the inverse Mills ratios by industry group using a similar methodology to that used in selection models of proportions data, which is discussed in Greene (1992). The methodology relies on the working assumption that all firms in the same industry-year expect to be selected with the same probability. Let $p_{it} \equiv \frac{N_{it}^{\mathcal{C}}}{N_{it}^{\mathcal{C}} + N_{it}^{\mathcal{P}}}$(i.e., p_{it} is the empirical proportion of public firms in industry i in a given year). Then the selection model is given by:

$$p_{it} = \Phi(\gamma_t \mathbf{z_{it}}) + \zeta_{it}, \tag{F1}$$

where $\mathbf{z_{it}}$ denotes the vector of industry-specific characteristics that determine the public status of firms in a given industry group, Φ denotes the normal cumulative density function, and ζ_{it} is a sampling error. As in Greene (1992), we treat the sampling of public firms within the same industry as a problem of sampling from a Bernoulli population. Hence ζ_{it} is such that $E[\zeta_{it}] = 0$ and $Var[\zeta_{it}] = \Phi(\gamma_t \mathbf{z_{it}})(1 - \Phi(\gamma_t \mathbf{z_{it}}))\left(N_{it}^{\mathcal{C}}\right)^{-1}$.

The model in F1 can be tested using non-linear least squares. However, as shown in Greene (1992), there is a simpler empirical approach using linear least squares. Given that the function Φ has an inverse, we use the alternative specification

$$\Phi^{-1}(p_{it}) \approx \gamma_t \mathbf{z_{it}} + \frac{\zeta_{\mathbf{it}}}{\phi(\gamma_{\mathbf{t}} \mathbf{z_{it}})}. \tag{F2}$$

We estimate the selection model in (F2) in multiple steps. As a first step, we run an OLS regression for each yearly cross-section of manufacturing industries in the U.S. Census Bureau (where p_i is observable) between 1960 and 2010. The vector z_i includes variables that explain the public status of firms.

The variables which we include in z_i are consistent with previous studies explaining the decision to go public. Since these variables should explain the *share* of public firms in the industry, we use both average industry characteristics of both private and public firms, or public firms only. The vector z_i includes the labor intensity of the industry computed using data from BEA; the industry growth in COMPUSTAT sales; the volatility in the industry growth of COMPUSTAT sales; the book leverage as measured by COMPUSTAT, the share of firms in the industry with positive expenses in RD; the share of firms with positive dividends in the industry; and the share of firms with zero financial debt in the industry. We describe the construction of these variables in Appendix E.

The vector z_i further includes four variables which we do not use in the vector x_i during the second stage of the sample selection correction. We argue that these variables relate to the going public decision but do not explain the level of sales in the second stage. These four variables are three dummies indicating the share of firms in the industry quoting on NASDAQ, NYSE and AMEX, respectively; and the industry contribution to total value added (i.e. the contribution of a given industry to GDP).

Since the errors of the OLS regression of our first step are heteroskedastic, we use the estimated coefficients $\hat{\gamma}_t$ of the OLS regression of $\Phi^{-1}(p_{it})$ on $\gamma_t \mathbf{z_{it}}$ to generate the sample weights w_{jt} defined as

$$w_{jt} = \frac{N_{it}^{C} \Phi(\hat{\gamma}_t \mathbf{z_{it}})^2}{\Phi(\hat{\gamma}_t \mathbf{z_{it}})(1 - \Phi(\hat{\gamma}_t \mathbf{z_{it}}))}. \tag{F3}$$

We then repeat the same linear regression in equation (F2) using the weights in (F3) as p-weights, to obtain the coefficients $\hat{\hat{\gamma}}_t$ for all years in our sample of manufacturing industries. We use our estimates $\hat{\hat{\gamma}}_t$ by year to construct the inverse Mills ratio, $\lambda_{it} \equiv \frac{\phi(\hat{\hat{\gamma}}_t \mathbf{z_{it}})}{\Phi(\hat{\hat{\gamma}}_t \mathbf{z_{it}})}$. and the statistic $v_{jt} \equiv 1 - \lambda_{it}\left(\lambda_{it} + \hat{\hat{\gamma}}_t \mathbf{z_{it}}\right)$ for all manufacturing industries.

Finally, we compute the corresponding statistics λ_{it} and v_{it} for all non-manufacturing industries. Since we do not observe p_{it} for these industries, we use the vector of instruments z_{it} and our estimates $\hat{\hat{\gamma}}_t$ to compute λ_{it} and v_{it} for the non-manufacturing industries. The working assumption is therefore that the estimates $\hat{\hat{\gamma}}_t$ are the same for all industries in a given year t.

To construct the CBC measure, we consider h_{ij} to be the logarithm of firms' Compustat sales. We know that the conditional mean of h_{ij} for public firms is given by:

$$\begin{aligned} E(h_{ijt} | j \in i \text{ is public}) &= \psi_t \mathbf{x_{it}} + \mathbf{E}\left(\varepsilon_{\mathbf{jt}} | \mathbf{j} \in \mathbf{i} \text{ is public}\right) \\ &= \psi_t \mathbf{x_{it}} + \rho_{\mathbf{it}} \sigma_{\mathbf{it}} \lambda_{\mathbf{it}}, \end{aligned} \tag{F4}$$

where $\rho_{it}\sigma_{it}$ is the covariance between ε_{jt} and u_{it}. Similarly, the conditional variance of h_{jit} for public firms is given by:

$$\begin{aligned} Var\left(h_{ijt}|j \in i \text{ is public}\right) &= E\left(e_{jt}^2|j \in i \text{ is public}\right) \\ &= \sigma_{it}^2\left[1-\rho_{it}^2\left(1-v_{it}\right)\right]. \end{aligned} \tag{F5}$$

We use the results of the OLS cross-sectional regressions of the log sales in Compustat on $\mathbf{x}$ and λ to compute the adjusted mean and variance in sales of public and private firms for all industry years. Given that the empirical methodology to correct for selection bias relies on the normality assumption, we use log sales in the OLS regressions since sales is highly skewed and the goodness-of-fit is higher when we use the variable in logs.

We use the results of the OLS regressions to construct the adjusted average sales for public and private by industry-year, $\hat{\mu}_{lnsales}$, and the adjusted industry variance in sales of public and private firms by industry-year, $\hat{\sigma}_{lnsales}$. Using the definition of the mean and variance of the log normal distribution function, we then apply these estimates to compute $\hat{\mu}_{sales}$ and $\hat{\sigma}_{sales}$.

We construct the CBC measure replacing for $\hat{\mu}_{sales}$ and $\hat{\sigma}_{sales}$ in the formula in equation (8). For those industries in which we do not observe the total number of firms (i.e. non-manufacturing industries), we obtain proxy of the number of firms in the industry $\hat{N}_{it}$ using the result from the first stage that:

$$\hat{N}_{it} \equiv \frac{N_{it}^C}{\Phi(\hat{\hat{\gamma}}_t \mathbf{z_{it}})}. \tag{F6}$$

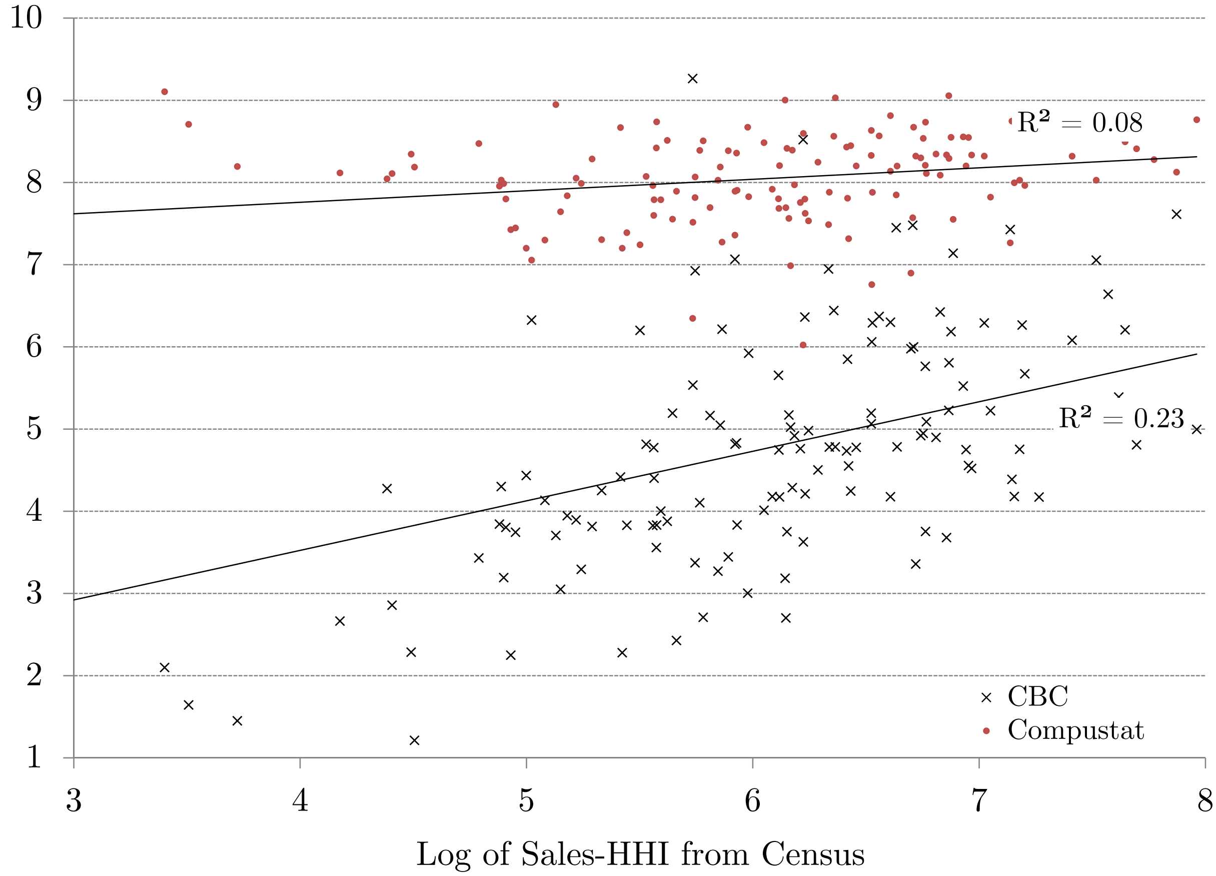
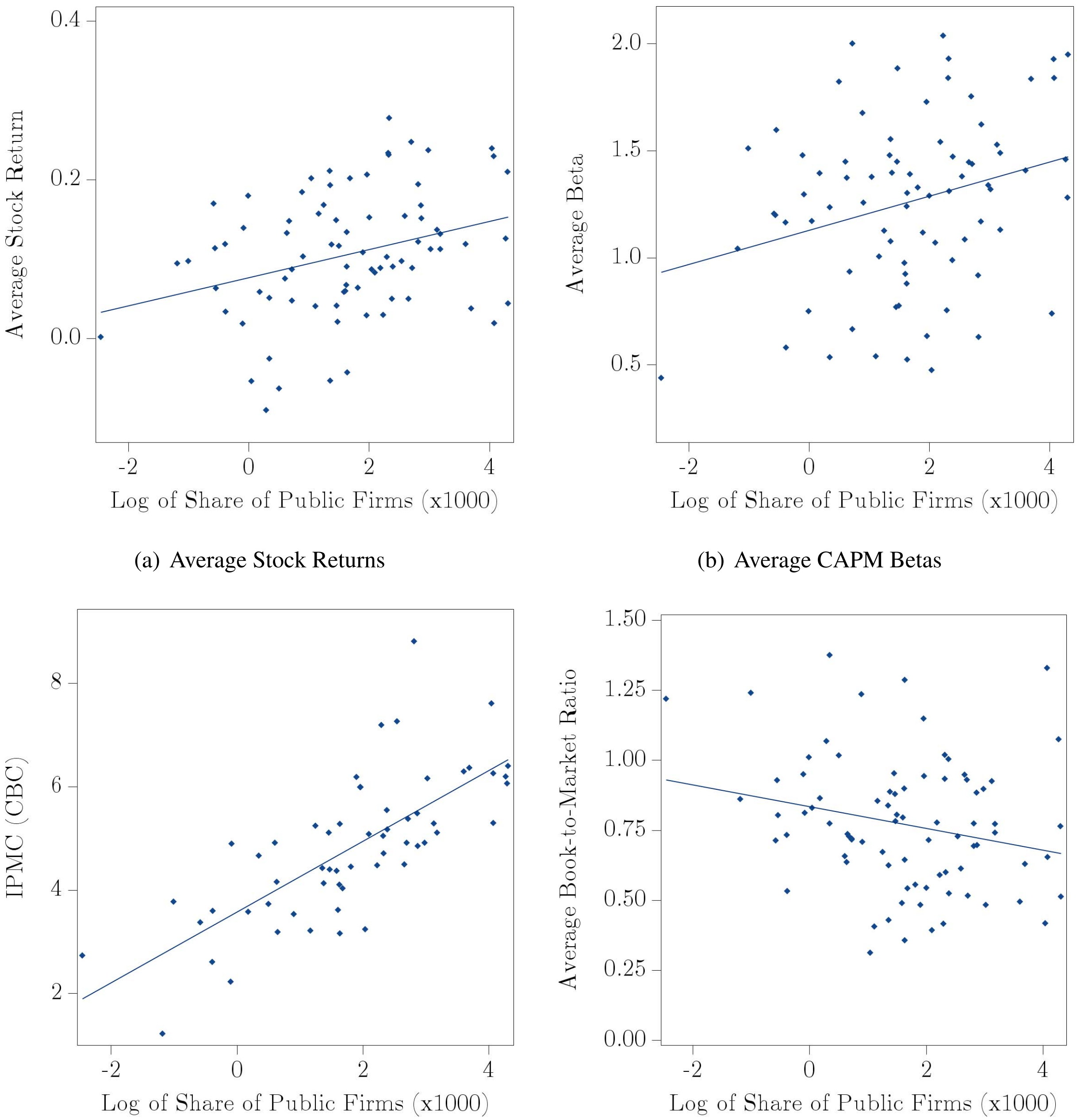


Figure 1. This plot shows the relation between the Characteristic-Based Concentration (CBC) measure, the Sales-HHI Index based on Compustat data, and the Sales-HHI Index based on Census data (HHI). Plot shows average statistics for manufacturing industries over the years 1982-2009.



(a) Average Stock Returns

(b) Average CAPM Betas

(c) Average Measure of IPMC (CBC)

(d) Average Book-to-Market Ratios

Figure 2. This plot shows the relation between the share of public firms to total firms in the industry to average betas, stock returns, book-to-market ratios, and the CBC measure of imperfect product market competition. The plot shows average industries over the years 2001-2009.

Table I
Most Competitive and Least Competitive Industries

The table presents the bottom and top 15 four-digit SIC industries sorted on measures imperfect product market competition, as of 2008.

Panel A: Sorts by Characteristic-Based Concentration (CBC)		
SIC	Industry Title	CBC
	Most Competitive Industries	
2721	Periodicals: Publishing, or Publishing and Printing	1.1
3531	Construction Machinery and Equipment	1.1
5712	Furniture Stores	1.1
2421	Sawmills and Planing Mills, General	1.2
2511	Wood Household Furniture, Except Upholstered	1.5
2711	Newspapers: Publishing, or Publishing and Printing	1.7
8741	Management Services	1.8
3911	Jewelry, Precious Metal	2.1
8011	Offices and Clinics of Doctors of Medicine	2.2
7948	Racing, Including Track Operation	2.2
3443	Fabricated Plate Work (Boiler Shops)	2.2
3442	Metal Doors, Sash, Frames, Molding, and Trim Manufacturing	2.3
3564	Industrial and Commercial Fans, Blowers, and Air Purification	2.5
2011	Meat Packing Plants	2.7
3713	Truck and Bus Bodies	2.8
	Least Competitive Industries	
2834	Pharmaceutical Preparations	9.4
4731	Arrangement of Transportation of Freight and Cargo	9.4
8731	Commercial Physical and Biological Research	9.4
8742	Management Consulting Services	9.4
4581	Airports, Flying Fields, and Airport Terminal Services	9.3
8071	Medical Laboratories	9.2
2911	Petroleum Refining	9.2
7812	Motion Picture and Video Tape Production	9.1
5093	Scrap and Waste Materials	9.0
4813	Telephone Communications, Except Radiotelephone	8.9
4841	Cable and Other Pay Television Services	8.9
5122	Drugs, Drug Proprietaries, and Druggists' Sundries	8.8
4513	Air Courier Services	8.7
4899	Communications Services, Not Elsewhere Classified	8.7
4011	Railroads, Line-Haul Operating	8.6

Table I
Most Competitive and Least Competitive Industries (Cont.)

	Panel B: Sorts by Concentration Markup Combined (CMC)	
SIC	Industry Title	CMC
	Most Competitive Industries	
2011	Meat Packing Plants	0.0
2421	Sawmills and Planing Mills, General	0.0
3713	Truck and Bus Bodies	0.0
2221	Broadwoven Fabric Mills, Manmade Fiber and Silk	0.1
3531	Construction Machinery and Equipment	0.1
3661	Telephone and Telegraph Apparatus	0.1
2452	Prefabricated Wood Buildings and Components	0.1
3081	Unsupported Plastics Film and Sheet	0.1
3442	Metal Doors, Sash, Frames, Molding, and Trim Manufacturing	0.1
3443	Fabricated Plate Work (Boiler Shops)	0.1
3448	Prefabricated Metal Buildings and Components	0.1
3555	Printing Trades Machinery and Equipment	0.1
3677	Electronic Coils, Transformers, and Other Inductors	0.1
3695	Magnetic And Optical Recording Media	0.1
2015	Poultry Slaughtering and Processing	0.1
	Least Competitive Industries	
2834	Pharmaceutical Preparations	1.0
2111	Cigarettes	0.8
3845	Electromedical and Electrotherapeutic Apparatus	0.7
2835	In Vitro and In Vivo Diagnostic Substances	0.7
3674	Semiconductors and Related Devices	0.7
2085	Distilled and Blended Liquors	0.6
3571	Electronic Computers	0.6
2836	Biological Products, Except Diagnostic Substances	0.6
2082	Malt Beverages	0.6
3663	Radio and Television Broadcasting and Communications Equip.	0.6
2844	Perfumes, Cosmetics, and Other Toilet Preparations	0.5
2842	Specialty Cleaning, Polishing, and Sanitation Preparations	0.5
3841	Surgical and Medical Instruments and Apparatus	0.5
2911	Petroleum Refining	0.5
3572	Computer Storage Devices	0.4

Table II
Summary Statistics of Firms Sorted on Industry Measures of Imperfect Competition

The table reports time-series averages of median characteristics of portfolio of firms sorted on industry measures of imperfect competition. *HHI* is the logarithm of the Herfindahl-Hirschman Index of sales of firms in the industry, *Markup* is the average industry markup, *CBC* is the Characteristic-Based Concentration measure, and *CMC* is the combined measure of *CBC* and *Markup*. *CMC* is constructed as the sum of the rank (0–20) of *Markup* and the rank (0–20) of *CBC* within each year. *TBC* is the text-based measure of competition from Hoberg and Phillips (2010b). *HHI Comp.* is the logarithm of the Herfindahl-Hirschman Index of sales of firms in the industry using Compustat data, constructed as in Hou and Robinson (2006). *Cap. Int.* is the ratio of payments to capital to industry GDP from data from BEA. *Log Asset* is the logarithm of book value of assets. *Log Size* is the logarithm of market value of equity plus book value of total debt. *B/M* is shareholders equity divided by market value of equity. *E/P* is earnings divided by market value of equity. *Lev.* is the ratio of book value of debt adjusted for cash holdings, as reported in Compustat, divided by the assets. OL^{Comp} is the measure of operating leverage from Novy-Marx (2011), defined as costs of goods sold plus sales, general, and administrative expenses over total assets. The sample covers the period 1965–2009, except for *HHI* that covers the period 1982–2009 and *TBC* that covers the period 1996 to 2008. The sample covers manufacturing only industries, except for *CBC* and *TBC* that cover all industries in Compustat except for financials, regulated, and mining.

Portfolio	Measure	HHI Comp.	Lab. Int.	Log. Asset	Log Size	B/M	E/P	Lev.	OL^{Comp}
Panel A: Sorts by Herfindahl-Hirschman Index (HHI)									
L	5.05	7.12	0.71	5.01	4.88	0.55	0.13	0.30	1.02
2	5.82	6.63	0.61	4.76	5.03	0.42	0.09	0.20	0.88
3	6.22	7.33	0.61	4.97	5.02	0.52	0.11	0.28	0.94
4	6.58	7.21	0.67	5.08	5.13	0.49	0.09	0.25	0.95
H	7.17	7.11	0.74	5.14	5.31	0.51	0.11	0.24	0.92
Panel B: Sorts by Industry Markup									
L	0.21	7.48	0.74	5.26	4.77	0.78	0.22	0.43	1.22
2	0.29	7.40	0.73	4.96	4.64	0.69	0.20	0.37	1.10
3	0.35	7.39	0.72	4.67	4.54	0.63	0.17	0.31	1.04
4	0.42	6.98	0.65	4.20	4.48	0.48	0.11	0.22	0.92
H	0.55	6.91	0.52	4.50	4.86	0.40	0.09	0.20	0.81
Panel C: Sorts by Characteristic-Based Concentration (CBC)									
L	3.64	7.48	0.72	4.95	4.56	0.65	0.19	0.38	1.22
2	4.98	7.28	0.72	4.83	4.59	0.62	0.17	0.34	1.12
3	5.91	7.25	0.74	4.85	4.68	0.62	0.17	0.33	1.07
4	6.74	7.30	0.72	4.73	4.73	0.55	0.15	0.31	0.98
H	7.88	7.08	0.57	5.06	5.09	0.51	0.14	0.29	0.89
Panel D: Sorts by Concentration Markup Combined (CMC)									
L	0.19	7.50	0.72	4.88	4.40	0.75	0.21	0.41	1.24
2	0.35	7.49	0.74	4.81	4.55	0.67	0.18	0.34	1.08
3	0.47	7.33	0.74	5.06	4.89	0.62	0.17	0.33	1.02
4	0.61	6.99	0.71	4.61	4.74	0.54	0.13	0.25	0.90
H	0.85	6.89	0.53	4.25	4.73	0.38	0.07	0.18	0.81
Panel E: Sorts by Text-Based Competition (TBC)									
L	1.07	7.65	0.69	5.73	5.56	0.49	0.13	0.32	1.00
2	1.32	7.56	0.71	6.10	5.91	0.53	0.14	0.33	0.99
3	1.86	7.32	0.71	6.05	6.02	0.52	0.12	0.29	0.93
4	3.26	7.14	0.73	5.87	5.98	0.46	0.09	0.24	0.84
H	8.19	6.83	0.65	5.10	5.74	0.33	0.02	0.12	0.67

Table III
Earnings-to-Price Ratio and Measures of Imperfect Industry Competition

The table shows estimates and standard errors of panel data regressions with year effects of earnings-to-price ratios on measures of imperfect competition and firm characteristics. *E/P* is earnings divided by market value of equity. *Res.* is the residual earnings to price ratio from model XI. λ is the inverse Mills ratio that controls for the sample-selection bias public firms. Remaining variables are described in Table II. Standard errors clustered by firm are shown in parenthesis. Significance levels are denoted by (* = 10% level), (** = 5% level), and (*** = 1% level). The sample covers the period 1966–2010 , except for *HHI* that covers the period 1983–2010 and *TBC* that covers the period 1997 to 2009. The sample covers manufacturing only industries, except for *CBC* and *TBC* that cover all industries in Compustat except for financials, regulated, and mining.

Measure	HHI		Markup		CBC		CMC		TBC		
Dep. Variable	E/P	Res.	E/P	Res.	E/P	Res.	E/P	Res.	E/P	Res.	E/P
Model	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
Measure_{t-1}	-0.15***	-0.10***	-3.34***	-1.88***	-0.25***	-0.14***	-2.27***	-1.45***	-0.13***	-0.07***	
	(0.02)	(0.02)	(0.17)	(0.13)	(0.01)	(0.01)	(0.08)	(0.07)	(0.01)	(0.00)	
Lab. Int._{t-1}	1.55***		0.63***		-0.14		-0.17		-1.36***		1.72***
	(0.26)		(0.17)		(0.20)		(0.17)		(0.26)		(0.19)
Log Asset_{t-1}	0.42***		0.34***		0.39***		0.35***		0.33***		0.86***
	(0.01)		(0.01)		(0.01)		(0.01)		(0.01)		(0.04)
λ_{t-1}											0.55***
											(0.03)
Year Eff.	Y	N	Y	N	Y	N	Y	N	Y	N	Y
R-sq. (%)	17.91	0.52	32.09	1.69	31.80	1.46	33.30	2.95	22.86	5.02	31.83
Obs.	22,029	22,029	36,159	36,159	40,756	40,756	35,950	35,950	15,759	15,759	54,534

Table IV
Book-to-Market Ratio and Measures of Imperfect Industry Competition

The table shows estimates and standard errors of panel data regressions with year effects of book-to-market ratios on measures of imperfect competition and firm characteristics. *B/M* is shareholders equity divided by market value of equity. *Res.* is the residual book-to-market ratio from Model XI. λ is the inverse Mills ratio that controls for the sample-selection bias public firms. Remaining variables are described in Table II. Standard errors clustered by firm are shown in parenthesis. Significance levels are denoted by (* = 10% level), (** = 5% level), and (*** = 1% level). The sample covers the period 1966–2010 , except for *HHI* that covers the period 1983–2010 and *TBC* that covers the period 1997 to 2009. The sample covers manufacturing only industries, except for *CBC* and *TBC* that cover all industries in Compustat except for financials, regulated, and mining.

Measure	HHI		Markup		CBC		CMC		TBC		
Dep. Variable	B/M	Res.	B/M	Res.	B/M	Res.	B/M	Res.	B/M	Res.	B/M
Model	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
Measure$_{t-1}$	-0.44***	-0.36***	-8.69***	-5.03***	-0.48***	-0.24***	-5.03***	-3.22***	-0.17***	-0.08***	
	(0.14)	(0.14)	(0.48)	(0.35)	(0.03)	(0.03)	(0.27)	(0.20)	(0.01)	(0.01)	
Lab. Int.$_{t-1}$	4.17***		2.87***		1.69***		1.46***		0.08		6.19***
	(0.58)		(0.45)		(0.47)		(0.47)		(0.58)		(0.49)
Log Asset$_{t-1}$	0.60***		0.51***		0.63***		0.56***		0.41***		1.73***
	(0.03)		(0.03)		(0.03)		(0.03)		(0.04)		(0.10)
λ_{t-1}											1.30***
											(0.08)
Year Eff.	Y	N	Y	N	Y	N	Y	N	Y	N	Y
R-sq. (%)	10.16	0.77	22.64	1.41	21.31	0.54	22.68	1.69	9.54	0.65	23.12
Obs.	22,079	22,079	36,226	36,226	40,832	40,832	36,006	36,006	15,809	15,809	54,643

Table V
Operating Leverage of Firms Sorted on Measures of Imperfect Industry Competition

The table reports average measures of operating leverage of firms sorted on lagged measures of imperfect competition. OL^{Comp} is the measure of operating leverage from Novy-Marx (2011), defined as costs of goods sold plus sales, general, and administrative expenses over total assets. OL^{TFP} a measure of operating leverage based on the NBER/CES data defined as the slope of rolling time-series regressions of changes in value added on changes in TFP. H-L is the difference between the average statistic of firms with high imperfect competition (H) and of firms with low imperfect competition (L). Newey-West standard errors are estimated with one lag. Significance levels are denoted by (* = 10% level), (** = 5% level) and (*** = 1% level). The sample covers the period 1966–2010 , except for *HHI* that covers the period 1983–2010 and *TBC* that covers the period 1997 to 2009. The sample covers manufacturing only industries, except for *CBC* and *TBC* that cover all industries in Compustat except for financials, regulated, and mining.

Portfolio	HHI		Markup		CBC		CMC		TBC	
	OL^{Comp}	OL^{TFP}	OL^{Comp}	OL^{TFP}	OL^{Comp}	OL^{TFP}	OL^{Comp}	OL^{TFP}	OL^{Comp}	OL^{TFP}
L	1.09	1.80	1.44	1.90	1.44	1.74	1.44	2.03	1.13	1.79
2	0.98	1.40	1.14	1.91	1.34	1.91	1.13	1.97	1.16	1.81
3	1.04	1.50	1.08	1.67	1.27	1.61	1.08	1.53	1.11	1.86
4	1.06	1.81	0.97	1.45	1.13	1.67	0.96	1.27	1.05	1.55
H	0.98	1.62	0.90	1.07	1.06	1.13	0.90	1.21	0.85	1.23
H-L	-0.11***	-0.17	-0.54***	-0.82***	-0.38***	-0.61***	-0.53***	-0.82***	-0.29***	-0.56***
	(0.02)	(0.20)	(0.02)	(0.15)	(0.07)	(0.09)	(0.02)	(0.08)	(0.02)	(0.02)

Table VI
Operating Leverage and Measures of Imperfect Industry Competition

The table shows estimates and standard errors of panel data regressions with year effects of a measure of operating leverage on measures of imperfect competition and firm characteristics. OL^{Comp} is the measure of operating leverage from Novy-Marx (2011), defined as costs of goods sold plus sales, general, and administrative expenses over total assets. *Res.* is the residual the measure of operating leverage from Model XI. λ is the inverse Mills ratio that controls for the sample-selection bias public firms. Remaining variables are described in Table II. Standard errors clustered by firm are shown in parenthesis. Significance levels are denoted by (* = 10% level), (** = 5% level), and (*** = 1% level). The sample covers the period 1966–2010 , except for *HHI* that covers the period 1983–2010 and *TBC* that covers the period 1997 to 2009. The sample covers manufacturing only industries, except for *CBC* and *TBC* that cover all industries in Compustat except for financials, regulated, and mining.

Measure	HHI		Markup		CBC		CMC		TBC		
Dep. Variable	OL^{Comp}	Res.	OL^{Comp}	Res.	OL^{Comp}	Res.	OL^{Comp}	Res.	OL^{Comp}	Res.	OL^{Comp}
Model	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
Measure$_{t-1}$	0.00	0.01***	-1.40***	-0.86***	-0.05***	-0.03***	-0.82***	-0.49***	-0.02***	-0.01***	
	(0.00)	(0.00)	(0.04)	(0.03)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	
Lab. Int.$_{t-1}$	-0.18***		-0.58***		-0.46***		-0.79***		-0.15***		-0.17***
	(0.03)		(0.03)		(0.03)		(0.03)		(0.03)		(0.02)
Log Size$_{t-1}$	-0.12***		-0.04**		-0.05***		-0.03*		-0.07***		0.05**
	(0.02)		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)
Log B/M$_{t-1}$	-0.10***		-0.06***		-0.05***		-0.06***		-0.09***		0.05***
	(0.01)		(0.01)		(0.01)		(0.01)		(0.02)		(0.01)
Log Asset$_{t-1}$	0.05**		-0.03*		-0.02		-0.04**		-0.01		0.04***
	(0.02)		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)
E/P$_{t-1}$	0.09***		0.16***		0.08***		0.12***		-0.12***		0.19***
	(0.03)		(0.02)		(0.02)		(0.02)		(0.03)		(0.02)
Leverage$_{t-1}$	0.05***		0.04***		0.06***		0.04***		0.08***		0.13***
	(0.01)		(0.00)		(0.00)		(0.00)		(0.01)		(0.01)
λ_{t-1}											0.08***
											(0.00)
Year Eff.	Y	N	Y	N	Y	N	Y	N	Y	N	Y
R-sq. (%)	14.74	0.05	22.99	4.81	18.44	0.81	23.30	4.56	17.12	1.53	16.99
Obs.	20,188	20,188	33,600	33,600	37,835	37,835	33,405	33,405	14,200	14,200	51,298

Table VII

Cross-Section of Returns of Stocks Sorted on Measures of Imperfect Industry Competition

The table reports post-ranking mean realized excess monthly stock returns over one-month Treasury bill rates, and adjusted monthly returns of portfolios of stocks sorted on lagged measures of imperfect competition. *ER* are portfolio returns minus the one-month Treasury bill, *DGTW* are returns adjusted for size, book-to-market, and momentum, according to the methodology in Daniel, Grinblatt, Titman, and Wermers (1997), *Unlev.* are unlevered returns calculated as excess returns times one minus book value of debt over assets minus book value of equity plus market value of equity. *Adj.* are returns adjusted for size, book-to-market, and operating margins (EBITDA / Assets). H-L is the zero investment portfolio long the portfolio of firms with high imperfect competition (H) and short the portfolio of firms with low imperfect competition (L). Newey-West standard errors are estimated with one lag. Significance levels are denoted by (* = 10% level), (** = 5% level) and (*** = 1% level). The sample covers the period 1966–2010 , except for *HHI* that covers the period 1983–2010 and *TBC* that covers the period 1997 to 2009. The sample covers manufacturing only industries, except for *CBC* and *TBC* that cover all industries in Compustat except for financials, regulated, and mining.

Panel A: Sorts Across All Firms

Portfolio	HHI		Markup		CBC		CMC		TBC	
	ER	DGTW	ER	DGTW	ER	DGTW	ER	DGTW	ER	DGTW
L	8.46	-1.22	8.59	-0.55	8.67	-0.63	8.24	-0.99	9.48	-1.92
2	11.99	3.44	8.34	-0.86	8.76	-0.38	7.93	-1.77	10.17	-1.85
3	10.52	2.07	10.05	1.08	10.64	1.21	9.56	1.26	12.70	-0.54
4	10.37	1.98	9.48	2.05	10.34	1.17	11.17	3.00	14.77	2.11
H	14.34	4.15	11.23	4.32	10.33	2.81	10.63	4.53	16.95	4.16
H-L	5.88	5.37	2.64	4.87*	1.66	3.43***	2.39	5.51*	7.47	6.09
	(3.88)	(3.72)	(3.39)	(2.67)	(1.51)	(1.09)	(3.47)	(2.97)	(8.26)	(6.20)
	Unlev.	Adj.	Unlev.	Adj.	Unlev.	Adj.	Unlev.	Adj.	Unlev.	Adj.
L	4.39	-1.97	3.00	-0.72	3.44	-1.06	3.28	-1.35	3.86	-2.36
2	7.94	3.43	3.73	-0.92	4.21	-0.24	3.54	-1.80	4.03	-2.24
3	5.11	2.64	5.02	0.58	5.03	1.09	4.31	0.78	6.14	-0.73
4	5.85	1.96	5.60	2.81	4.84	1.63	6.07	3.48	7.45	1.69
H	7.43	4.71	6.85	4.66	5.41	3.06	7.08	5.28	10.22	5.22
H-L	3.04	6.68*	3.84*	5.39**	1.97*	4.12***	3.80	6.63**	6.36	7.57
	(2.59)	(3.65)	(2.27)	(2.58)	(1.10)	(1.20)	(2.53)	(2.98)	(6.14)	(5.18)

Table VII
Cross-Section of Returns of Stocks Sorted on Measures of Imperfect Industry Competition (Cont.)

Panel B: Sorts Within 5 Groups of Firms Sorted on Size										
Portfolio	HHI		Markup		CBC		CMC		TBC	
	ER	DGTW	ER	DGTW	ER	DGTW	ER	DGTW	ER	DGTW
L	9.45	-0.69	8.48	-0.64	8.44	-0.71	7.84	-1.20	9.76	-1.50
2	10.71	2.67	9.12	-0.32	8.55	-0.63	8.15	-1.53	10.06	-1.86
3	11.46	2.84	9.17	0.50	10.72	1.17	10.03	1.18	11.81	-1.27
4	9.53	1.06	9.22	1.90	10.36	1.39	9.74	2.23	16.51	2.84
H	14.72	4.52	11.72	4.50	10.61	2.88	11.94	5.25	16.04	3.60
H-L	5.27	5.22	3.24	5.14*	2.17	3.59***	4.10	6.45**	6.27	5.10
	(3.59)	(3.39)	(3.35)	(2.69)	(1.38)	(1.13)	(3.62)	(3.19)	(7.23)	(5.45)
	Unlev.	Adj.	Unlev.	Adj.	Unlev.	Adj.	Unlev.	Adj.	Unlev.	Adj.
L	5.04	-1.38	2.97	-0.86	3.45	-1.11	3.06	-1.49	3.86	-2.06
2	7.01	2.72	4.13	-0.49	3.98	-0.48	3.66	-1.53	4.11	-2.09
3	5.96	3.16	4.65	0.09	5.14	1.22	4.56	0.88	5.72	-1.26
4	5.27	1.07	5.33	2.68	4.97	1.71	5.32	2.38	8.29	2.35
H	7.76	5.03	7.13	4.76	5.40	3.01	7.65	6.02	9.76	4.35
H-L	2.72	6.41*	4.15*	5.62**	1.96*	4.12***	4.59*	7.51**	5.90	6.42
	(2.45)	(3.40)	(2.32)	(2.58)	(1.05)	(1.19)	(2.63)	(3.18)	(5.61)	(4.61)

Table VIII
Annual Stock Returns and Measures of Imperfect Industry Competition

The table shows estimates and standard errors of panel data regressions with year effects of stock returns on measures of imperfect competition and firm characteristics. *Res.* is the residual return from model XI. λ is the inverse Mills ratio that controls for the sample-selection bias public firms. Remaining variables are described in Table II. Standard errors clustered by firm are shown in parenthesis. Significance levels are denoted by (* = 10% level), (** = 5% level), and (*** = 1% level). The sample covers the period 1966–2010 , except for *HHI* that covers the period 1983–2010 and *TBC* that covers the period 1997 to 2009. The sample covers manufacturing only industries, except for *CBC* and *TBC* that cover all industries in Compustat except for financials, regulated, and mining.

Measure	HHI		Markup		CBC		CMC		TBC		
Dep. Variable	Ret.	Res.	Ret.	Res.	Ret.	Res.	Ret.	Res.	Ret.	Res.	Ret.
Model	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
Measure_{t-1}	0.92***	0.75**	22.93***	9.24***	1.58***	0.65***	14.24***	5.87***	0.71***	0.23*	
	(0.32)	(0.30)	(3.22)	(2.64)	(0.20)	(0.17)	(1.61)	(1.39)	(0.16)	(0.13)	
Lab. Int._{t-1}	-7.34**		-3.29		4.56*		0.66		14.08***		-4.87
	(3.52)		(2.77)		(2.72)		(2.80)		(4.73)		(2.69)
Log Size_{t-1}	-7.04***		-4.11**		-2.66		-4.55**		-7.71**		-5.57
	(2.68)		(1.92)		(2.02)		(1.94)		(3.60)		(2.11)
Log B/M_{t-1}	0.93		3.06**		2.99**		2.87**		-1.03		-0.29***
	(1.74)		(1.23)		(1.22)		(1.24)		(2.39)		(1.39)
Log Asset_{t-1}	6.97***		3.67*		1.93		3.95**		6.74*		-3.19
	(2.64)		(1.91)		(2.01)		(1.92)		(3.56)		(2.10)
E/P_{t-1}	0.32		1.87		0.91		2.70		-6.34		-1.13*
	(2.95)		(2.02)		(2.01)		(2.03)		(4.37)		(2.09)
Leverage_{t-1}	-2.65***		-0.91*		-0.59		-1.02**		-1.65*		-4.41
	(0.71)		(0.50)		(0.54)		(0.51)		(0.99)		(0.86)
λ_{t-1}											-4.16***
											(0.41)
Year Eff.	Y	N	Y	N	Y	N	Y	N	Y	N	Y
R-sq. (%)	11.26	0.02	13.67	0.05	13.58	0.03	13.69	0.06	13.76	0.03	13.33
Obs.	20,307	20,307	33,630	33,630	37,718	37,718	33,433	33,433	14,261	14,261	50,627

Table IX

Average Conditional Betas of Stocks Sorted on Measures of Imperfect Industry Competition

The table reports average conditional betas of portfolios stocks sorted on lagged measures of imperfect competition. *Beta* are the betas with respect to the market risk factor from Kenneth French's website. *Unlev.* are unlevered betas, calculated as beta times one minus book value of debt over assets minus book value of equity plus market value of equity. H-L is the zero investment portfolio long the portfolio of firms with high imperfect competition (H) and short the portfolio of firms with low imperfect competition (L). Newey-West standard errors are estimated with one lag. Significance levels are denoted by (* = 10% level), (** = 5% level) and (*** = 1% level). The sample covers the period 1966–2010 , except for *HHI* that covers the period 1983–2010 and *TBC* that covers the period 1997 to 2009. The sample covers manufacturing only industries, except for *CBC* and *TBC* that cover all industries in Compustat except for financials, regulated, and mining.

Portfolio	HHI		Markup		CBC		CMC		TBC	
	Beta	Unlev.	Beta	Unlev.	Beta	Unlev.	Beta	Unlev.	Beta	Unlev.
					Panel A: Sorts Across All Firms					
L	1.55	1.00	1.56	0.88	1.54	0.92	1.56	0.90	1.43	0.92
2	1.65	1.24	1.59	0.97	1.63	1.02	1.63	1.03	1.48	0.96
3	1.66	1.17	1.57	1.05	1.66	1.06	1.52	0.98	1.55	1.05
4	1.70	1.18	1.72	1.27	1.68	1.11	1.75	1.24	1.72	1.23
H	1.83	1.30	1.69	1.28	1.58	1.07	1.69	1.31	1.96	1.63
H-L	0.28***	0.29***	0.13	0.40***	0.04	0.15*	0.13	0.40***	0.53**	0.72***
	(0.09)	(0.09)	(0.10)	(0.09)	(0.08)	(0.08)	(0.10)	(0.10)	(0.19)	(0.17)
					Panel B: Sorts Within 5 Groups of Firms Sorted on Size					
L	1.55	1.01	1.57	0.87	1.52	0.91	1.54	0.90	1.43	0.92
2	1.60	1.18	1.58	0.96	1.61	1.00	1.60	1.00	1.51	0.97
3	1.62	1.15	1.59	1.05	1.65	1.05	1.53	0.98	1.56	1.04
4	1.79	1.26	1.72	1.26	1.68	1.10	1.77	1.24	1.72	1.24
H	1.83	1.29	1.69	1.28	1.62	1.09	1.70	1.31	1.92	1.59
H-L	0.28***	0.28***	0.12	0.40***	0.10	0.18**	0.16*	0.41***	0.49**	0.68***
	(0.08)	(0.08)	(0.09)	(0.08)	(0.07)	(0.08)	(0.09)	(0.09)	(0.18)	(0.17)

Table X
Conditional Beta and Measures of Imperfect Industry Competition

The table shows estimates and standard errors of panel data regressions with year effects of conditional betas on measures of imperfect competition and firm characteristics. *Beta* is conditional beta, defined as the slope of univariate 12 month rolling regressions of excess returns on the market portfolio one year ahead. *Res.* is the residual conditional beta from model XI. λ is the inverse Mills ratio that controls for the sample-selection bias public firms. Remaining variables are described in Table II. Standard errors clustered by firm are shown in parenthesis. Significance levels are denoted by (* = 10% level), (** = 5% level), and (*** = 1% level). The sample covers the period 1966–2010 , except for *HHI* that covers the period 1983–2010 and *TBC* that covers the period 1997 to 2009. The sample covers manufacturing only industries, except for *CBC* and *TBC* that cover all industries in Compustat except for financials, regulated, and mining.

Measure	HHI		Markup		CBC		CMC		TBC		
Dep. Variable	Beta	Res.	Beta	Res.	Beta	Res.	Beta	Res.	Beta	Res.	Beta
Model	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
Measure$_{t-1}$	0.18*	0.11	4.57***	0.18	0.67***	0.16***	4.94***	1.39***	0.49***	0.22***	
	(0.10)	(0.10)	(0.90)	(0.74)	(0.07)	(0.06)	(0.51)	(0.45)	(0.04)	(0.03)	
Lab. Int.$_{t-1}$	4.66***		8.03***		11.59***		10.35***		20.82***		7.02***
	(1.12)		(0.84)		(0.92)		(0.87)		(1.21)		(0.88)
Log Size$_{t-1}$	0.36		0.03		0.06		-0.11		3.56***		-1.88
	(0.92)		(0.66)		(0.65)		(0.66)		(0.86)		(0.71)
Log B/M$_{t-1}$	-0.25		-0.68*		-0.64		-0.66		1.22**		-2.88*
	(0.59)		(0.41)		(0.41)		(0.41)		(0.56)		(0.49)
Log Asset$_{t-1}$	-1.55*		-1.33**		-1.45**		-1.24*		-4.72***		-3.85***
	(0.92)		(0.66)		(0.65)		(0.66)		(0.86)		(0.71)
E/P$_{t-1}$	-8.57***		-5.51***		-4.82***		-5.17***		-6.56***		-6.43***
	(1.33)		(0.82)		(0.79)		(0.82)		(1.37)		(0.80)
Leverage$_{t-1}$	0.60**		0.75***		0.70***		0.76***		2.00***		-1.24***
	(0.26)		(0.18)		(0.18)		(0.18)		(0.25)		(0.29)
λ_{t-1}											-2.22***
											(0.13)
Year Eff.	Y	N	Y	N	Y	N	Y	N	Y	N	Y
R-sq. (%)	6.93	0.00	7.73	0.00	8.23	0.02	7.89	0.03	9.69	0.53	8.39
Obs.	19,722	19,722	32,693	32,693	36,541	36,541	32,501	32,501	13,693	13,693	48,954

Table XI

Beta Decomposition of Firms Sorted on Measures of Imperfect Industry Competition

The table reports the decomposition of unlevered conditional betas of portfolios stocks sorted on lagged measures of imperfect competition into assets in place and growth option betas (Panel A) and weights of fixed operating costs ("operating leverage") and growth options (Panel B). The beta decomposition adapts the methodology in Bernardo, Chowdhry, and Goyal (2007) to decompose betas into revenue and growth betas as in Novy-Marx (2011), assuming that fixed cost betas is zero. H-L is the difference between the average statistic of firms with high imperfect competition (H) and of firms with low imperfect competition (L). Newey-West standard errors are estimated with one lag. Significance levels are denoted by (* = 10% level), (** = 5% level) and (*** = 1% level). The sample covers the period 1966–2010 , except for *HHI* that covers the period 1983–2010 and *TBC* that covers the period 1997 to 2009. The sample covers manufacturing only industries, except for *CBC* and *TBC* that cover all industries in Compustat except for financials, regulated, and mining.

Portfolio	HHI		Markup		CBC		CMC		TBC	
Panel A: Betas										
	Assets in Place	Growth Options	Assets in Place	Growth Options	Assets in Place	Growth Options	Assets in Place	Growth Options	Assets in Place	Growth Options
L	0.53	1.40	0.46	1.36	0.48	1.43	0.48	1.41	0.53	1.34
2	0.55	1.50	0.54	1.54	0.51	1.51	0.55	1.51	0.52	1.35
3	0.54	1.42	0.56	1.51	0.55	1.57	0.53	1.46	0.54	1.41
4	0.55	1.48	0.57	1.55	0.56	1.58	0.60	1.59	0.60	1.49
H	0.64	1.64	0.61	1.52	0.52	1.49	0.57	1.51	0.68	1.57
H-L	0.12***	0.24***	0.14***	0.15**	0.04*	0.05	0.10***	0.10	0.15***	0.23***
	(0.03)	(0.04)	(0.03)	(0.06)	(0.02)	(0.04)	(0.03)	(0.07)	(0.03)	(0.06)
Panel B: Weights (%)										
	Fixed Costs	Growth Options	Fixed Costs	Growth Options	Fixed Costs	Growth Options	Fixed Costs	Growth Options	Fixed Costs	Growth Options
L	34.4	32.1	48.6	11.6	42.0	23.2	47.0	15.4	30.9	37.7
2	25.2	47.8	41.1	21.1	39.9	25.2	40.8	22.0	32.0	35.5
3	30.7	37.2	37.2	27.0	38.0	27.2	36.9	27.0	30.8	36.2
4	32.1	34.9	29.0	40.2	34.3	32.6	31.9	34.0	27.6	42.0
H	30.9	35.8	24.8	46.5	31.3	35.7	23.6	49.4	19.5	54.3
H-L	-3.4***	3.7*	-23.8***	34.9***	-10.7***	12.5***	-23.5***	34.0***	-11.4***	16.7***
	(1.2)	(1.9)	(1.6)	(2.7)	(1.5)	(2.8)	(1.7)	(3.2)	(1.7)	(3.9)