Asset Pricing with Entry and Imperfect Competition[†]

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Abstract

I study the implications of fluctuations in new firm creation across industries on asset prices. I write a general equilibrium model with heterogeneous industries, allowing for firm entry and time variation in markups. Firms entering an industry increase competition and displace incumbents' monopoly rents. This mechanism is strongest in industries that exhibit both a high elasticity of firm entry to aggregate fluctuations and a high elasticity of profits to new firm entry. I test the model using micro-level data on entry rates and industry portfolios and I find the price of entry risk is negative. Industries with more exposure to the risk of entry carry a 5.8 percent risk premium. The effect is strongest for industries where both the entry and the profit elasticities are high. I estimate the model using the simulated method of moments and confirm the role of both elasticities in shaping the cross section of industry returns.

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1 Introduction

Business dynamism and the innovation of new firms are a vital engine of economic growth, an idea that goes back to Schumpeter (1942) and figures prominently in the modern growth literature in Stokey (1988), Grossman and Helpman (1992), and Aghion and Howitt (1992), among others. While ultimately economic growth through innovation benefits the aggregate economy, it involves substantial reallocation at the microeconomic level. New firms compete with incumbents, reducing their monopoly power and taking away part of their rents. Investors are aware of such risks: In his 2007 Chairman's letter to the board of Berkshire Hathaway, Warren Buffett writes:

> "A truly great business must have an enduring "moat" that protects excellent returns on invested capital. The dynamics of capitalism guarantee that competitors will repeatedly assault any business "castle" that is earning high returns. (...). Our criterion of "enduring" causes us to rule out companies in industries prone to rapid and continuous change."

Not all industries are exposed to the competitive risk of new entrants; incumbents in some industries erect barriers to entry to insulate themselves from the risk of displacement. In this paper, I show how asset prices inform us about the risk of increased competition across industries. There is a large systematic component in firm entry rates across industries and the price of this risk factor is negative and quantitatively significant: investors command a large positive risk premium of 5.75% (in annualized returns) for holding an industry portfolio exposed to the risk of displacement over a portfolio insulated from this risk.

To investigate the economic underpinnings of differences in risk premia across industries, I develop an asset pricing model with endogenous entry and imperfect competition. Firms earn monopolistic rents that vary across industries. These rents determine firms' valuations. New firms decide to enter based on ex post monopoly rents and the cost of starting up a firm. As new firms enter an industry, they increase competition such that in equilibrium the marginal cost of entry equals the marginal benefit of monopoly rents.

First I ground the model in the data and collect micro level data on establishments at the four-digit NAICS industry code level from the Quarterly Census of Employment and Wages (QCEW) from the Bureau of Labor Statistics (BLS). There is a strong factor structure across industry entry rates: the first two principal components account for more than 40% of the total variation. I jointly estimate the entry aggregate factor and the different exposures of industry to this factor. While this procedure does not explicitly uncover the economic underpinnings of the entry factor, I interpret its innovations as news shocks for entrepreneurs that push them to start up new firms. I find differences in industries' exposure where firm creation in some industries is very responsive to aggregate fluctuations: these industries have a high supply elasticity of new firms because their barriers to entry are low. I also document differences across industries in the response of profits to an influx of new competitors. I estimate this elasticity of firm profits to industry entry directly on public firms using COMPUSTAT matched with the QCEW at the four-digit industry code level. Intuitively, a new competitor will have a larger impact on competition if the product market is very concentrated than if it is already competitive, leading to variation across industries.

I build on models of international trade (see Melitz (2003)) to introduce a new asset pricing framework based on free entry and cash flows earned from monopolistic rents. Then

I show how to parsimoniously incorporate the two empirical stylized facts on the cross-section of industries in a model. I add two essential ingredients to the standard model: a supply of new entrants that is not perfectly elastic to fit the differences in the entry elasticity and markups that depend on the equilibrium product market to fit the difference in profit elasticity. In the model I show how both elasticities are necessary to assess the risk of an industry: the large entry elasticity to aggregate shocks of an industry is risky only if this translates into an effect on rents through a rise in competition.

To tie these two characteristics to asset prices and derive the industry risk premium, I show the aggregate cost of entry is a systematic risk factor. After a shock that increases the productivity of the innovation sector, aggregate resources are shifted from consumption good production towards firm creation. This reallocation process lowers consumption contemporaneously and can, under some conditions, increase the marginal utility of the representative investor. Hence firms in industries exposed to aggregate entry shocks will see their cash flow plunging after such positive shock, due to both a large influx of new firms and a large decline in monopoly rents. Since in these states of the world consumption is expensive to the representative investor, investors command a risk compensation for holding these firms in their stock portfolio: firms in industries that are highly exposed to entry earn higher risk premia in equilibrium.

I test the reduced form predictions of the theoretical framework by forming portfolios of industries sorted by their entry elasticity and by their profit elasticity. I confirm that entry risk is quantitatively important and that both industry entry elasticity and profit elasticity play a role in shaping industry returns: firms in industries with high entry elasticity earn on average annual returns that are 3.4% higher than firms in industries with low elasticity; likewise, firms with high profit elasticity earn average annual returns that are 2.4% higher than firms with low profit elasticity. To confirm that this premium does not reflect loadings on well known risk factors, I estimate the residual of stock excess returns from the five factor model of Fama and French (2015). I find that the high minus low entry elasticity portfolio generates returns of 8.2% annually, and that the high minus low profit elasticity portfolio generates returns of 4.7% annually. These findings hold for different measures of the entry factor and for different subperiods in the sample. Importantly, they also hold when portfolios are value weighted, which suggests that entry shocks matter for investors' wealth. Moreover I find both elasticities jointly affect industry returns. These two dimensions of entry enrich the findings of Bustamante and Donangelo (2017) and Corhay et al. (2015) on cash flow risk. If two industries have different profit elasticity but are not exposed to the entry risk factor, that is their entry elasticity is small, then I find no significant differences in their returns. Finally, to estimate formally the quantity of entry risk, I use a large cross section of industry test assets. I find an additional unit of exposure to the aggregate entry shock commands an additional risk compensation of 0.2 to 0.8 percent annually. I conclude that the risk of entry is priced in the cross section of expected returns, and that the performance of firms exposed to these shocks covaries negatively with investors' marginal utility.

Finally, I estimate the model using the simulated method of moments. I match entry elasticity, profit elasticity, average excess returns, average markups, and entry and exit rates for four different sectors. I emphasize how the two elasticities documented in the data across industries —the entry elasticity and the profit elasticity—map into the cross-section of asset returns in the model: an increase of one standard deviation in the entry elasticity of an industry leads to a 1.8% higher risk premium; similarly for the profit elasticity, a increase of one standard deviation in elasticity leads to a risk premium that is 3.5% higher.

In summary, my results illustrate how the cross section of industry returns identifies aggregate entry shocks through their differential effect on industries. I propose a novel mechanism for the volatility of cash-flows and stock returns across industries, leading to a risk-based explanation for the puzzling heterogeneity in the cost of capital across industries.

Related Literature. This essay revisits empirical asset pricing studies that link industrial organization to stock returns. The extant literature is mostly empirical, as in Fama and French (1997), who cast as a puzzle the sources of differences in returns across industries or Hou and Robinson (2006), who find that product market concentration is a predictor of lower returns in the cross section of industry returns. While these two papers follow the established tradition of structure, conduct, and performance methodology in industrial organization, my work brings a structural view of the relation between product markets and stock returns. My contribution on this front is methodological and borrows from the modern industrial organization approach to deliver predictions based on fundamental parameters of industries.[1]

My work complements the findings of Bustamante and Donangelo (2017) (BD) and Corhay et al. (2015) (CKS). They show that cash flow risk is crucial to our understanding of both the cross-section (BD) and time series (CKS) of industry returns. My direct measure of the profit elasticity largely overlaps with theirs (concentration ratios, Herfindahl index, and markups) and I confirm their empirical results: cash flow risk leads to higher average returns. Further, I find that the entry elasticity — the exposure of industries to aggregate risk — not only magnifies the effect of profit elasticity on returns but also of BD's and CKS's measures. Thus, my work contributes to the existing literature as it articulates some of the earlier findings in a dynamic general equilibrium model.

A nascent literature recognizes the importance of studying the risk of firms at the industry level. Other work by Bena et al. (2016), Garlappi and Song (2017), Opp et al. (2014) highlight the role of product markets as an amplification mechanism of aggregate fluctuations. In this paper, I reconcile both view of the literature in a dynamic general equilibrium model that ties industry dynamics to two structural industry elasticities, entry and profits, and asset prices. Binsbergen (2016) takes a different approach and uses good specific habits rather than product market structure to generate time variation in demand elasticities and link firms' price setting to asset prices. My contribution to this literature is also methodological. I show how to incorporate models from "new new" trade theory (e.g., Melitz (2003), Eaton and Kortum (2002)) with rich firm dynamics and monopoly rents into a standard general equilibrium asset pricing framework.[2]

This paper also sheds a new light on the production based asset pricing literature. Recent work emphasizes the importance of displacement risk to account for asset prices; see, for example, Berk et al. (1999), Gomes et al. (2003), Papanikolaou (2011), Gârleanu et

[1] See Bresnahan (1989) for a survey on the Structure-Conduct-Performance paradigm and Berry and Reiss (2007) for a modern approach to the link between entry and market structure.

[2] See, for example, Barrot et al. (2019) and Bretscher (2019) for applications of this framework to link international trade and asset prices.

al. (2012a), Gârleanu et al. (2012b), Kogan et al. (2018). The supply side of the economy usually features a neoclassical production function in a competitive environment with capital investments at the intensive margin.[3] The current literature has focused on mechanisms where the price of displacement risk is negative. Here, I propose a new view of displacement risk where monopolistic rents are exposed to innovation through the extensive margin, firm entry, rather than the intensive margin, capital investment. Thus while keeping the familiar framework of asset pricing with production, my model generates new empirical implications centered specifically on industry characteristics.

Outline. The structure of the paper is as follows: in Section 2, I document two facts on the dynamics of entry across industries and I introduce the two key statistics that I will show to shape returns. In Section 3, I present the theoretical framework and I derive its main implications for asset prices. In Section 4, I test the reduced form asset pricing implications of the model and confirm that entry risk is relevant. Finally in Section 5, I estimate the model using the simulated method of moments to assess the model quantitatively. All proofs and derivations are in Appendix A.

2 Measurement and Empirical Motivation

In this paper, I develop a theory of the risk of entry dynamics and I use a cross section of industries to test my predictions. Entry of new competitors is risky for incumbent firms as they steal market shares and lower product prices. However this risk will only be reflected in asset prices to the extent it is systematic. So first I show how the dynamics of entry across industries share a common aggregate component. Then I zoom in at the firm level and document how incumbent firms are exposed to the risk of competition by new entrants. While firms in some industries tend to lose 7% for a 1% increase in firm entry, some firms in other industries show no response. These two main facts are the backbone of my model which separates industries by their differential exposure to a aggregate entry factor and the risk of their profits to new entrants.

2.1 Measuring Exposure to Entry

I use micro-level data on establishments by industries from the Quarterly Census of Employment and Wages (QCEW) from the Bureau of Labor Statistics.[4] This dataset reports the number of establishments in each four-digit NAICS level at a quarterly frequency. The sample covers the period from 1992 to 2017 and includes 303 industries.

Using the QCEW I estimate quarterly entry rates by industries. I find that there is a strong factor structure in entry rates across industries: the first two principal components of the panel account for 40% of the total variation in entry rates. Not all industries share the same exposure to the aggregate entry factors, thus I use the interactive fixed effect

[3] One exception is Gârleanu et al. (2012a) where the set of intermediate goods expands exogenously which is close to Romer (1990). However, the paper focuses on the household side and the imperfect risk sharing among generations.

[4] Details of the data construction are in the Appendix Section B.1.

methodology developed in Bai (2009) to estimate jointly the factors and their loadings given the panel structure of my data. The econometric specification is:

$$\Delta M_{ht} = \mathbf{Z}'_{ht}\beta + u_{ht}$$
$$u_{ht} = a_h + \zeta_h \mathbf{F}_t + \varepsilon_{ht},$$

where ΔM_{ht} is the entry rate (based on establishments) in a given industry; $\mathbf{Z}_{ht}$ is a vector of industry controls which include the past number of establishments $M_{h,t-1}$ and aggregate productivity; I also allow for industry fixed effects in the form of a_h to control for unobserved heterogeneity at the industry level. I jointly estimate the model to find both a cross section of loadings $(\zeta_h^{(1)}, \zeta_h^{(2)}, \dots)$ for each industry i which corresponds to each factor $\mathbf{F}_t = (F_t^{(1)}, F_t^{(2)}, \dots)$. I focus on the first two factors and I find that $F^{(1)}$ is strongly correlated with aggregate output. In Table 1, I present the correlation of both factors with three different measures of aggregate output and while the first factor exhibits a high level of correlations with all measures, the second factor $F^{(2)}$ presents no significant correlations.[5] Thus the second factor is the best candidate to capture an entry specific shock that is distinct from general movements in aggregate productivity.[6]

Table 1
Correlation of the Entry Factors with Aggregate Output

Table 1 presents estimates of the pairwise correlation between three output variables (growth rate) and the entry factor estimated from a panel of entry rates at the industry level. ΔY is the growth rate of output from Fernald (2012), ΔGDP is the growth rate of gross domestic product (BEA), ΔC is the growth rate of consumption, both from NIPA. IST is the investment-specific-technological change from Papanikolaou (2011).

	ΔY	ΔGDP	ΔC	$\mathbf{F}^{(1)}$	$\mathbf{F}^{(2)}$	IST
ΔY	—	0.589	0.593	0.381	0.000	0.306
ΔGDP		—	0.824	0.545	0.160	0.227
ΔC			—	0.634	0.093	0.264
$\mathbf{F}^{(1)}$				—	0	0.110
$\mathbf{F}^{(2)}$				0	—	0.020

I am interested in both the role of the aggregate entry factor and the fact that different industries are differentially exposed to aggregate entry. Preempting the empirical analysis of Section 4, I present summary statistics of firms across industries with different ζ_i in Panel A of Table 2. I find no significant differences across most of the firm level observable characteristics—size, book-to-market, leverage, and investment—between the more exposed industries and the least exposed ones. Note that financial profitability is slighty lower for the more risky firms, as are average industry markups. More importantly, the volatility of markups in industries that load more on the entry factor is significantly higher (31%) than for industries with small exposure (17.2%). Note that average equity returns show a

[5] See Figure 4 for a time series of the main entry factor.

[6] While the entry shock share similarities with investment-specific technological change (e.g. Papanikolaou (2011)), it is quantitatively different; the correlation with the two factors is close to zero.

similar pattern: firms in exposed industries have returns that are higher by 3.4% than firms in low exposure industries. I also present some illustrative examples of industries with a large exposure to aggregate entry in Panel A of Appendix Table C.1. One such industry is *Software Publishers* whose entry cyclicality loads heavily on the aggregate entry shock. Both facts will serve as a building block of the model in Section 3. Finally I estimate the elasticity of industry entry directly on the entry factor estimated above and confirm that factor loadings do predict how firm entry responds to the entry factor.

2.2 Measuring the Response of Profits to Entry

I now turn to how entry actually affects firms. I estimate the elasticity of firms' profitability to entry at the industry level in the following econometric specification:

$$\Delta \mathrm{CF}_{i,h,t+1} = \eta_h M_{h,t} + \mathbf{X}_{it}' \beta + a_h + a_t + \varepsilon_{i,t}.$$

I follow Fama and French (2006) to predict cash flow growth at the firm level. I leave details of the data construction to the empirical Section 4.1 and Appendix B.1. I consider all public firms from the COMPUSTAT quarterly FUNDQ file. Cash flow at the firm level is defined as earnings before interest and taxes scaled by the total value of assets. I include the following firm level regressors, $\mathbf{X}_{it}$, book-to-market, dividends scaled by the book value of the firm, a dividend dummy, and time, as well as four-digit NAICS industry fixed effects (a_t and a_h). The elasticity η summarizes the effect of industry entry on profitability at the firm level, and differentiates the impact of entry across industries. Some industries have large exposures ζ to the aggregate entry factor, yet the effect of entry on profitability for these industries is small. Thus these industries face little risk of entry. I show summary statistics of different industries with different entry elasticity η in Panel B of Table 2. The findings of Panel B echo those of Panel A. Firms do not differ along size, book-to-market, leverage, or investment or average markups. Firms in riskier industries do have lower profitability and more volatile markups. The latter result confirms the relevance of our measure since we find that industries where we find firms whose cash flows respond significantly to entry, also have more volatile price-cost markups. We also find that industries whose firms have riskier cash flows also have higher returns, 13.2% annualized, compared to firms with low measured elasticity η, 10.8%. An illustrative example of an industry whose profits are very elastic to competition is *Local Messengers and Local Delivery* (see Panel B of Appendix Table C.1). I will build on these facts as a building block of the firm level microfoundation in the model.

3 Modeling Framework

Overview. I build on international trade models featuring an explicit extensive margin of capital investment as in Melitz (2003), Bilbiie et al. (2012). Firms earn monopolistic rents that depend on the structure of the industry. These rents or profits determine firms' stock price in equilibrium. There is entry into each industry such that new firms decide to enter based on ex post monopoly rents. As they enter an industry, new firms compete with incumbents and alter the industry equilibrium driving down monopoly rents, reducing incumbents' profits and stock prices. I represent an overview of the structure of the economy from firm creation to consumption in Figure 1.

I use the evidence from the past section to introduce two departures from the standard model of firm entry. First, I introduce convex adjustment costs at the entry margin to account for the different response ζ of entry to aggregate shocks documented in Section 2.1 above. Second, I move away from the Dixit-Stiglitz constant elasticity of substitution (CES) framework that imposes fixed markups. With generalized preferences, monopoly rents vary in response to the change in competition in an industry; this novel approach allows me to match the empirical counterpart of Section 2.2 that shows there is significant heterogeneity across industries of the response of profits to new firm entry.

Finally I include these features in a general equilibrium asset pricing framework and derive clear asset pricing implications of the entry risk across industries that differ across the two dimensions emphasized in Section 2: the ζ elasticity of entry to the aggregate and the η elasticity of profits to entry.

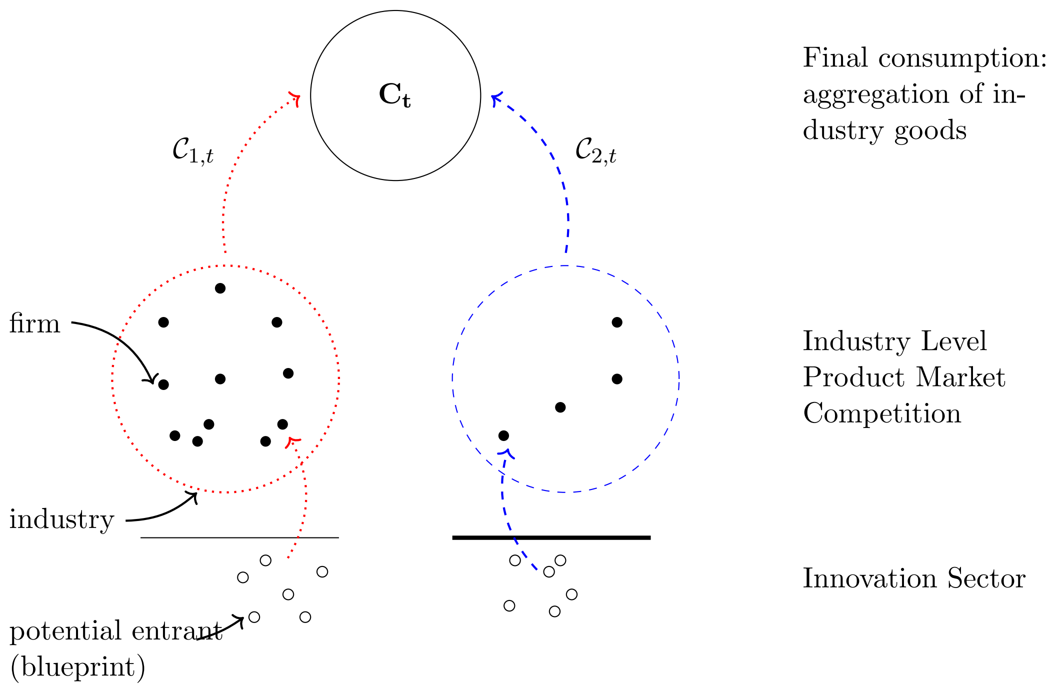

Figure 1. An overview of the structure of the economy for two industries (red and blue): from firm creation to industry competition to consumption.

3.1 Model Setup

3.1.1 Households

Intratemporal Consumption Choice. The economy is divided into industries indexed by $h \in \{1, \dots, H\}$. In each industry there is a continuum of firms, and each of these firms produces a differentiated good indexed by ω. There exists a continuum of identical households in the economy. They have nested preferences and decide on their consumption basket optimally: first they maximize their utility at the industry level, choosing their consumption over the set of available varieties within the industry. Then they choose their consumption at the aggregate level, given an upper-tier preference over industry level consumption indexes. Finally, the static utility from the upper-tier utility constitutes the final aggregate consumption index. Households consider this aggregate index for their intertemporal decisions.

Consumption Choices Within Industries. In each industry, households maximize their utility $\mathcal{C}_h$ from consuming differentiated varieties ω from industry h given a level of expenditure E_h. They take as given their total level of industry expenditure E_h and the mass of available varieties $\Omega_h = [0, M_h]$:

$$\mathcal{C}_h = \max_{\{c_h(\omega)\}} \int_0^{M_h} f_h(c_h(\omega), \mathbf{C}_h)\mathrm{d}\omega, \qquad \text{such that} \quad \int_0^{M_h} p_h(\omega)c_h(\omega)\mathrm{d}\omega \leq E_h,$$

where M_h is the total number (or mass) of goods producing firms in sector h, $c_h(\omega)$ is consumers' demand for variety ω, $p_h(\omega)$ the variety price, and total consumption $\mathbf{C}_h = \int_0^{M_h} c_h(\omega)\mathrm{d}\omega$.[7] This type of preference over a continuum of differentiated goods is a generalization of Dixit-Stiglitz preferences exposed in Zhelobodko et al. (2012). The generalization departs from the classical framework of Dixit-Stiglitz where markups are constant. I assume the aggregator over differentiated varieties is of the form, $f_h(x, \mathbf{X}) = \frac{\sigma_h}{\sigma_h - 1} x^{1-1/\sigma_h} - \overline{M}_h^{1/\sigma_h} x \, \mathbf{X}^{-1/\sigma_h}$. While the aggregator form is not very explicit, it is easier to think with its mathematical dual, the price elasticity of demand, $\mathcal{E}_h$:

$$\mathcal{E}_h(\omega) := -\frac{\partial \log c_h(\omega)}{\partial \log p_h(\omega)} = \sigma_h \cdot \left(1 - \left(\frac{M_h}{\overline{M}_h}\right)^{-1/\sigma_h}\right). \tag{3.1}$$

This generalization solves the problem of fixed markups inherent to CES aggregators and I detail in Section 3.3.2 below how it allows (a) the demand elasticity and thus markups vary with the number of firms within an industry; (b) the elasticity of markups to firm entry M_h is also industry specific. This generalization is relatively parsimonious as I only introduce one new scaling parameter at the industry level: $\overline{M}_h$. In the benchmark case of a CES aggregator, this elasticity is fixed and equal to σ_h. Here the demand elasticity is always smaller than σ_h, and as the number of firms in an industry increases, the elasticity increases. As the number of outside options increases, consumers find it easier to switch to different varieties, and become more price sensitive.

The parameter $\overline{M}_h$ determines the scale of the product market space. For large values of $\overline{M}_h$, industry h is a large product market that can accomodate many firms —for example, an industry with multiple differentiated segments that appeal to different customers. Thus an increase in the number of firms in this industry will have a small effect on the consumer demand elasticity. In the extreme case of $\overline{M}_h = 0$, the demand elasticity is highest and fixed at σ_h: the product market is saturated and each new entrant will steal market shares

[7] I drop the time subscript for clarity in all optimization pertaining to intra-temporal choices but these quantitites are moving over time as the structure of the industry changes.

from incumbents, given the standard static demand elasticity parameter σ_h. On the other hand, for large values of $\overline{M}_h$, the elasticity can go to zero whenever the scale of the product market is as large as the number of firms in it: $\lim_{\overline{M}_h \to M_h} \mathcal{E}_h = 0$. In this case each firm operates on its fully differentiated segment and consumers are completely inelastic within a segment.

As I detail below, this departure from standard Dixit-Stiglitz CES preferences is essential to capture different responses of firm profits to new entrants across industries, the η elasticity measured above in Section 2.2. Finally while these industry preferences generalize the CES framework, they remain very tractable and the indirect utility function keeps the key property of a constant elasticity with respect to the industry expenditure level E_h. Therefore the model remains simple as I am able to derive closed form aggregate consumption index from an upper-tier CES aggregator over industry level utilities.

Consumption Choices Across Industries. In each period, consumers maximize utility derived from the consumption of goods from H industries and derive the following aggregate consumption index:

$$C = \prod_{h=1}^{H} \left[s_h \mathcal{C}_h \right]^{\frac{\alpha_h}{s_h}} , \tag{3.2}$$

where $\sum_h \alpha_h = 1$ and s_h is an industry taste shifter.

Intertemporal Consumption Choice. The representative household has recursive preferences of the Epstein and Zin (1989) type. He maximizes his continuation utility J_t over sequences of the consumption index C_t:

$$J_t = \left[(1-\beta) C_t^{1-\nu} + \beta \left(\mathsf{R}_t(J_{t+1}) \right)^{1-\nu} \right]^{\frac{1}{1-\nu}} ,$$

where β is the time-preference parameter and ν is the inverse of the elasticity of intertemporal substitution (EIS). $\mathsf{R}_t(J_{t+1}) = [\mathbf{E}_t\{J_{t+1}^{1-\gamma}\}]^{1/(1-\gamma)}$ is the risk-adjusted continuation utility, where γ is the coefficient of relative risk aversion. I use Epstein and Zin (1989) preferences to disentangle the risk characteristics of households across states, and across time. The representative household supplies L units of labor inelastically each period in a competitive labor market, at wage w_t. Units of labor are freely allocated between the production in the consumption good sectors, (L_h^p), and the innovation sectors, (L_h^e), in each industry h:

$$\sum_h L_{h,t}^p + L_{h,t}^e = L.$$

3.1.2 Firms: Consumption Goods Sector

In the economy, production has two main purposes: the supply of consumption goods and the supply of new firms to industries, such that firm entry is dynamic. I represent both the consumption and the innovation sector at the bottom of Figure 1.

In the production of consumption goods, a firm in an industry is identified with the one variety ω it produces. Firms are infinitesimal within their industry and I assume they operate in a monopolistic competitive environment. They take consumers' demand curve (see equation 3.1) and input prices as given. Firms operate a linear production technology in labor, their sole factor input, as follows:

$$y_h(\omega) = A\ l_h(\omega),$$

where $y_h(\omega)$ is firm production of variety ω in industry h. Labor is subject to an exogenous productivity process and evolves according to an autoregressive process in logarithms, $\log A_{t+1} = \rho_A \log A_t + \sigma_A\, \varepsilon^A_{t+1}$, where ε^A_t is an i.i.d. process with standard deviation σ_A, and $\rho_A < 1$, such that $\log A_t$ is stationary. Firms hire labor at market wage w and maximize their static profit, $\pi_h(\omega) = p_h(\omega)y_h(\omega) - wl_h(\omega)$. In a monopolistically competitive market structure, firms take consumers' demand curve $c_h(\omega)$ as given. They produce $y_h(\omega) = c_h(\omega)$ and set their price $p_h(\omega)$ at a markup $\mu_h(\omega)$ over marginal cost, $p_h(\omega) = \mu_h(\omega)\frac{w}{A}$.

Markups are determined by consumers' demand curve, specifically their price elasticity of demand. In the case of a high price elasticity of demand, consumers are very price sensitive and it is hard for firms to extract much surplus from their monopolistic positions, which translates into lower markups. To gather intuition about firms' pricing decisions, I anticipate the static equilibrium. All firms are identical within an industry and set the same price, such that $p_h(\omega) = p_h$ and $y_h(\omega) = y_h$ and in consequence $\mathcal{E}_h(\omega) = \mathcal{E}_h$ and $\mu_h(\omega) = \mu_h$. This allows for a simple characterization of markups in equilibrium, since they only depend on consumers' demand curve.

$$\mu_h = \frac{p_h}{w/A} = \frac{\mathcal{E}_h}{\mathcal{E}_h - 1}$$

I provide details of the derivation of the static industry equilibrium in appendix A.1. Note that markups depend not only on the elasticity of substitution σ_h, but also on the level of competition through M_h. The net markup for Dixit-Stiglitz CES preferences is $1/\sigma_h$, which is a special case of our framework when $\overline{M}_h = 0$.

3.1.3 Innovation Sector

Entry. There are H different innovation sectors; each one is specialized to a single industry in the economy. In an innovation sector, there is a continuum of entrepreneurs endowed with a specialized technology. They transform blueprints into consumption firms in their industry of expertise. The cost of taking a mass M^e_h of blueprints and making them viable consumption firms in industry h are convex; I specify the labor requirement for introducing a given mass of blueprints and discuss the implications of the functional form below:

$$L^e_{h,t} = \frac{1}{X_t}\Phi_h(M^e_{h,t}, M_{h,t}) = \frac{1}{X_t}\frac{\exp(f_{e,h})}{1+\zeta_h^{-1}}\left(\frac{M^e_{h,t}}{M_{h,t}}\right)^{1+\zeta_h^{-1}} M_{h,t}. \tag{3.3}$$

The process X_t is the aggregate productivity of the innovation sector. It is common to entrepreneurs across all industries and follows an autoregressive process in logarithm, $\log X_{t+1} = \rho_X \log X_t + \sigma_X \varepsilon^X_{t+1}$, where ε^X_t is an i.i.d. process with standard deviation σ_X, and $\rho_X < 1$, such that $\log X_t$ is stationary. A positive shock $\varepsilon_t^X > 0$ to X_t increases the productivity of new firm creation in the whole economy.[8]

The cost of entry equation is akin to the cost of capital adjustment encountered in the literature (see Jermann (1998)). First there is an industry specific cost level $f_{e,h}$. Differences in $f_{e,h}$ correspond to changes in the absolute cost to enter the industry. In equilibrium, this determines the level of the average firm value in an industry, and through the entry first order condition, the average number of firms in the industry.

Second, the cost is convex in the entry rate M_h^e/M_h, and the convexity is governed by ζ_h^{-1}. The convexity parameter governs the elasticity of entry rates to changes in the marginal valuation of consumption firms in the industry.[9]

Entrepreneurs are in fixed supply, normalized to one. They earn rents on their concave "start-up" technology. The value of an entrepreneur $v_{h,t}^e$ represents a claim to the fixed supply of firm creation.[10] Their optimization program is simple as they maximize their value by choosing an entry rate and hiring the required labor inputs. Within an industry entrepreneurs are competitive and they take wages, w_t, and the price of a consumption good producing firm, $v_{h,t}$ as given. They are infinitesimal, thus they do not internalize the effect of their decisions on the current or future value of consumption firms in the industry. It follows that they maximize their static profit each period: $\max_{M_{h,t}^e} v_{h,t} M_{h,t}^e - w_t L_{h,t}^e$, subject to the cost equation (3.3). The first order condition of the entrepreneurs reads:

$$v_{h,t} = \frac{w_t}{X_t} \partial_1 \Phi_h(M_{h,t}^e, M_{h,t}) = \frac{\exp(f_{e,h}) w_t}{X_t} \left(\frac{M_{h,t}^e}{M_{h,t}} \right)^{\zeta_h^{-1}} . \tag{3.4}$$

From this equation, we recognize how ζ_h captures the elasticity of the firm entry rate M_h^e/M_h to a shock to X the aggregate productivity in the entry sector. It is the direct theoretical counterpart of the ζ measure I have highlighted in Section 2.1 above. Unlike standard models with an entry margin, in which the supply of entry is perfectly elastic, the introduction of an inelastic supply curve for entrants generates time variation in rents to incumbent firms.[11] These monopoly rents are shared between insiders—the incumbent firms— and outsiders—the entrepreneurs.

[8] The functional form for the entry costs is smooth from the point of view of the representative entrepreneur. Although smoothness is attractive for analytical tractability, it is not a realistic feature for the extensive margin of investment. Some of the literature on the extensive margin of investment also argues that at a disaggregated level, most of the costs are fixed; see, for example, Khan and Thomas (2008) and Bloom (2009). However, smoothness of entry costs at the industry level does not preclude one from having a fixed cost at the disaggregated entrepreneur level. Following this interpretation, each of the infinitesimal entrepreneurs face fixed costs of firm creation that are distributed like the aggregate marginal cost curve.

[9] The diminishing returns to scale of entrepreneurs' efficiency with respect to the absolute level of entry can also be interpreted as Venture Capitalists (VCs) monitoring start-ups before selling them on capital markets. Sahlman (1990) and Lerner (1995) show most of VCs' activity is spent monitoring startup projects. In a world with a fixed supply of VCs, monitoring has to be shared between all the firm creation projects in the industry.

[10] Alternatively, I could consider that entrepreneurs need industry-specific land for firm creation. If this industry-specific land is in fixed supply, normalized to one, the value of entrepreneurs is a claim to the land used to create new firms.

[11] In classic models of firm entry dynamics (see, e.g., Hopenhayn (1992), Melitz (2003)) costs of entry are fixed and the supply is perfectly elastic whenever incumbents' value is above the fixed costs.

Exit and Timing. In each industry, consumption goods firms are subject to an exogenous death shock at a rate δ. The shock hits firms at the end of the period. Firms do not face fixed costs to operate, and exit is entirely driven by this exogenous shock.

Entrants produced at time t face the same death shock as incumbents. Hence the dynamics for the mass of firms in industry h is given by the following accumulation equation:

$$M_{h,t+1} = (1-\delta)\left(M_{h,t} + M^e_{h,t}\right).$$

3.2 Competitive Equilibrium

I solve for the competitive equilibrium of the economy.[12] First I solve for the static intratemporal allocations given an aggregate consumption choice $\mathcal{C}_t$, and a product market structure $\{M_{h,t}\}$. Given the static allocations I derive the dynamic allocations of the extensive margin of investment through $\{M^e_{h,t}\}$ and aggregate consumption. The investment-consumption trade off is driven by the monopolistic rents at the industry level.

3.2.1 Static Equilibrium

Industry Equilibrium. Within industry h, firms are identical and they have identical pricing decisions. In appendix A.1, I derive the symmetric equilibrium conditions for a given level of industry expenditure E_h and a given mass of firms M_h:

$$p_h(\omega) = p_h = \frac{\mathcal{E}_h}{\mathcal{E}_h - 1}\cdot\frac{w}{A}, \qquad \pi_h(\omega) = \pi_h = \frac{1}{\mathcal{E}_h}\cdot\frac{E_h}{M_h}.$$

I show indirect utility follows:

$$\mathcal{C}_h = \left(\frac{AE_h}{wM_h}\cdot(1-\mu_h(M_h))\right)^{\frac{\sigma_h-1}{\sigma_h}}\cdot\frac{\sigma_h}{\sigma_h-1}M_h\cdot\left(1-\frac{\sigma_h-1}{\sigma_h}\left(\frac{M_h}{\overline{M}_h}\right)^{-\frac{1}{\sigma_h}}\right)$$

The industry level indirect utility $\mathcal{C}_h$ has constant elasticity with respect to the level of expenditures. This property of industry preferences allows for aggregation with multiple industries as I show hereafter.

Aggregate Equilibrium. I take aggregate consumption C as the numeraire of the economy each period. With the price of aggregate consumption equal to one, aggregate consumption is equal to total expenditures: $C = \sum_h E_h$. Households maximize their utility over expenditures across the different industries and the first order conditions are:

$$\frac{\partial C}{\partial E_h} = \frac{\alpha_h}{s_h}\cdot\frac{C}{\mathcal{C}_h}\cdot\frac{\partial\mathcal{C}_h}{\partial E_h}$$

In general the last term depends on equilibrium quantity and prices in the industry. With the preferences specified in (3.1), it simplifies to $(\sigma_h-1)/\sigma_h\cdot\mathcal{C}_h/E_h$. If we assume that the

[12]The planner allocation shows that there are distortions due to the dynamic and static inefficiencies of markups. I examine this issue in a companion note.

taste shifters are inversely related to markups as $s_h = (\sigma_h = 1)/\sigma_h$, industry expenditures are a constant fraction of total expenditures, just like in the standard Cobb-Douglas case:

$$E_h = \alpha_h C$$

To conclude the static equilibrium derivation, I write the local demand in each industry given the market structure M_h and the aggregate consumption choice C:

$$c_h = \frac{A}{w}\left(1 - \mu_h(M_h)\right) \cdot \frac{\alpha_h}{M_h} \cdot C \tag{3.5}$$

3.2.2 Dynamic Equilibrium

Consumption Sector. There are H mutual funds specializing in the consumption goods sector, and H mutual funds in the innovation sector. For each sector, a mutual fund owns all firms of an industry. Funds collect profits from firms—either entrepreneurs or consumption goods producers depending on their specialization—and redistribute them to their shareholders. Households can invest in $x_{h,t}$ shares of a mutual fund specializing in industry h for a price $x_{h,t}(M_{h,t} + M^e_{h,t})v_{h,t}$. Proceeds from the fund flow back to the shareholders and are equal to the profits made by all firms within an industry: $x_{h,t}M_{h,t}(v_{h,t} + \pi_{h,t})$. Households also invest $x^e_{h,t}$ shares in mutual funds specializing in entrepreneurs of industry h. The price of $x^e_{h,t}$ shares is $x^e_{h,t}v^e_{h,t}$ (the supply of entrepreneurs is fixed at one). Proceeds from this investment are $x^e_{h,t}\pi^e_{h,t}$.

Hence the representative household faces a dynamic program, the maximization of their continuation utility J_t subject to the following sequential budget constraint:

$$\begin{aligned}\sum_h \left[\int_0^{M_{h,t}} p_{h,t}(\omega)\ c_{h,t}(\omega)d\omega + x_{h,t+1}v_{h,t}\frac{M_{h,t+1}}{1-\delta} + x^e_{h,t+1}v^e_{h,t}\right] \\ \leq w_t L + \sum_h \left[x_{h,t}M_{h,t}(v_{h,t} + \pi_{h,t}) + x^e_{h,t}(v^e_{h,t} + \pi^e_{h,t})\right].\end{aligned} \tag{3.6}$$

I derive the one-period-ahead stochastic discount factor (SDF) from the household intertemporal Euler equation:

$$\frac{S_{t+1}}{S_t} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\nu}\left(\frac{J_{t+1}}{\mathsf{R}_t(J_{t+1})}\right)^{\nu-\gamma}. \tag{3.7}$$

I give details of the derivation of the household optimization condition in appendix A.1. The Bellman equation for pricing the consumption-goods firms in industry h is

$$v_{h,t} = (1-\delta)\mathbf{E}_t\left\{\frac{S_{t+1}}{S_t}\left(v_{h,t+1} + \pi_{h,t+1}\right)\right\}. \tag{3.8}$$

Innovation Sector. Entrepreneurs earn rent on their fixed supply specialized technology, which is rebated to the households. Households purchase stocks in new firms at market price with the rents, satisfying the budget constraint (3.6). Entrepreneurs equalize their marginal benefit of starting up a new firm in industry $v_{h,t}$, to their marginal cost of hiring labor to that process. This is summarized in the first order condition for entrepreneurs derived above in equation (3.4). The price of a firm in industry h does not only depend on the demand side from (3.8) but also from the supply and the incentives to enter into an industry. In this economy the incentives to innovate determine the stock price of firms in an industry. I analyze the link between incentives to innovate and industry asset prices in the next section.

3.2.3 Formal Competitive Equilibrium Definition

The competitive equilibrium is a sequence of prices, $(p_{h,t}, w_t, v_{h,t}, v^e_{h,t})$, and allocations, $(c_{h,t}, \mathcal{C}_{h,t}, C_t, L^e_{h,t}, L^p_{h,t}, M^e_{h,t}, M_{h,t}, x_{h,t}, x^e_{h,t})$; such that given the sequence of shocks $(\varepsilon^A_t, \varepsilon^X_t)$, (a) allocations maximize the households program (b) consumption-goods firms maximize profits (c) entrepreneurs maximize their value, (d) the labor, good, and asset markets clear, and (e) resources constraints are satisfied.

3.3 Inspecting the Model Mechanisms

The model introduces two new mechanisms to the asset pricing literature: first, the dynamics of industry entry with respect to aggregate factors, summarized by the statistics ζ in the data; second, the elasticity of profits to new firms summarized by the statistics η. After discussing how the model's microfoundations lead to heterogeneity in both elasticities, I turn to the sources of aggregate risk induced by the entry shock.

3.3.1 The Dynamics of Industry Entry: ζ

As stated above in Section 3.1.3, the entrepreneurs' first order condition determines the response of industry entry to aggregate economic conditions. If either the marginal productivity of entry, or the valuation of incumbent firms, are high in an industry, then firm creation will increase. Restating the first order condition (3.4) to focus on entry sheds light on the role of the elasticity parameter ζ_h:

$$\log\left(\frac{M^e_{h,t}}{M_{h,t}}\right) = \zeta_h \log\left(\frac{X_t}{w_t}\right) + \zeta_h \log v_{h,t} - \zeta_h f_{e,h}. \tag{3.9}$$

Small values of the elasticity ζ_h mean entry is inelastic and does not respond to either changes in incumbent firm valuations $v_{h,t}$, or to aggregate entry shocks X_t.[13] For large values of ζ_h, entry rates are, on the contrary, very elastic. Even small variations in industry firm valuations or aggregate entry shocks generate large changes in entry rates in industry h. In the limit of perfectly elastic entry, when ζ_h goes to infinity, the valuation of a firm is directly linked to the marginal cost of entry, such that $v_{h,t} = \exp(f_{e,h})w_t/X_t$.[14] In this case we recover standard models such as Melitz (2003) where entry is perfectly elastic and valuations are fully determined by fixed entry costs.

An imperfectly elastic supply curve introduces a wedge between the value of firm inside an industry, $v_{h,t}$ and its value outside (the marginal cost of starting up a firm for an

[13]See Appendix Figure A.1 for a graphical representation of the intuition for the mechanism.

[14]Note that the fixed cost parameter, $f_{e,h}$ governs the level of the supply curve, not its shape. As discussed in the case of a perfectly elastic supply, it pins down the price but not its dynamics. I use the parameter to adjust the average profit rate across industries.

entrepreneur). This mechanism is closely related to the literature on the q-theory of investment: with investment at the firm level, the wedge between the value of (intensive) capital inside and outside a firm depends on the level of adjustment costs.

The novelty of my framework lies in the flexibility of the industry elasticity for the supply of "capital". The model is able to match the variation in entry elasticity present in the data that I have documented in Section 2.1, which is not the case for a standard model with an entry margin.

3.3.2 The Elasticity of Firm Profit: η

The response of entry to systematic shocks, that is to the aggregate entry factor X_t, only matters if ultimately new entrants have an effect on incumbent firms. Firms are negatively affected by entry because of an increase in competition; however the data shows that the impact of competition on firms' profits vary greatly across industries as shown in Section 2.2. I incorporate a new ingredient in the model that captures this heterogeneity of the profit response in the data. The elasticity of consumer demand curves increase with the number of firms competing in a given industry. If more firms enter an industry, the product market becomes more crowded and consumers can easily switch from one variety to the next, leading to a greater demand elasticity. There is a direct parallel to the Salop circle model where new entrants increase the density of the product market space making it easier for consumers to switch products.

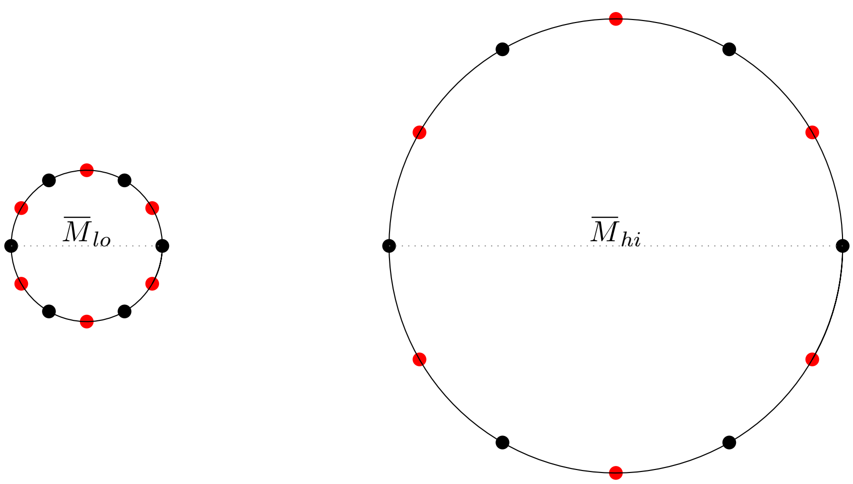

Figure 2. The role of $\overline{M_h}$ on the product market structure: analogy to the Hotelling/Salop model. On the left panel I represent a small product market (small circle circumference $\overline{M}_{lo}$) with a small distance between products as the new products (in read) are introduced leading to a larger demand elasticity $\mathcal{E}_h$. On the right panel, the product market space is larger and the demand elasticity is smaller.

Formally the elasticity of consumer demand and markups follow:

$$\mathcal{E}_h(\omega) = -\frac{\partial \log c_h(\omega)}{\partial \log p_h(\omega)} = \sigma_h \cdot \left(1 - \left(\frac{M_h}{\overline{M}_h}\right)^{-1/\sigma_h}\right)$$

The parameter σ_h is the limit level for the elasticity of substitution across varieties within industry h, while parameter $\overline{M}_h$ represents the size of the product market (the circumference of the circle in Salop's model). In the Dixit-Stiglitz case of a CES aggregator, the elasticity of demand curves is constant equal σ_h. The demand curve $\mathcal{E}_h$ here nests the Dixit-Stiglitz as an upper bound in the limiting case of perfectly saturated markets when either the number of firms operating in the industry M_h is very large ($\lim_{M_h \to \infty} \mathcal{E}_h = \sigma_h$) or when the product market space $\overline{M}_h$ is very small ($\lim_{\overline{M}_h \to 0} \mathcal{E}_h = \sigma_h$). The demand curve features three important properties that affect how firms' profits respond to new entrants that I discuss below: (a) it is increasing in M_h; (b) it is concave in M_h; (c) it is decreasing in the overall size of the product space $\overline{M}_h$.

First as the number of firms that operate in an industry increase the elasticity of consumer demand increases. Markups are a decreasing function of the demand elasticity:

$$\mu_h = \frac{p_h}{w/A} = \frac{\mathcal{E}_h}{\mathcal{E}_h - 1}. \tag{3.10}$$

Thus as the number of firms increase markups decline and so does the profit of incumbent firms.

Second, as more firms enter an industry the effect of the marginal entrant on consumer demand diminishes: the demand elasticity is concave in M_h. Figure 3 represents the demand elasticity $\mathcal{E}_h$ as a function of the number of firms in the industry M_h for different parameter values of σ_h and $\overline{M}_h$; it illustrates the concavity of the demand curve and how for a large number of firms, new entrants have little effects on demand. This is a key and intuitive results: in a very concentrated industry, the marginal effect of a new entrant can be very large as it will disrupt an oligopolistic market structure. But in an industry where there is already a large number of firms competing, the effect of a new entrant on competition will be small as prices will be close to their competitive limit.

Finally it is important to understand how the model maps into its empirical counterpart η. In Section 2.2 we capture differences across industries in the elasticity of profits to an extra firm. In the model this elasticity takes the following form:

$$\frac{\partial \log \pi_h}{\partial \log M_h} = -1 - \frac{\partial \log \mu_h}{\partial \log M_h} = -1 - \frac{1}{\sigma_h} \cdot \frac{1}{\overline{M}_h^{-1/\sigma_h} \cdot M_h^{1/\sigma_h} - 1} \tag{3.11}$$

There are two effects of an increase in entry on profits: a direct and an indirect effect. First, a one percent increase in the number of firms will reduce the level of monopoly rent per firm by one percent: this is the standard business stealing effect present in the Dixit-Stiglitz framework. The demand elasticity varies with the number of firms, and a one percent increase in the number of firms will affect the total level of monopoly rents that can be extracted from consumers. The size of this effect depends on both σ_h and $\overline{M}_h$. The comparative statics analysis with respect to σ_h are ambiguous (the effect decreases with σ_h for small values of M_h and increases for large values). However it decreases monotonously

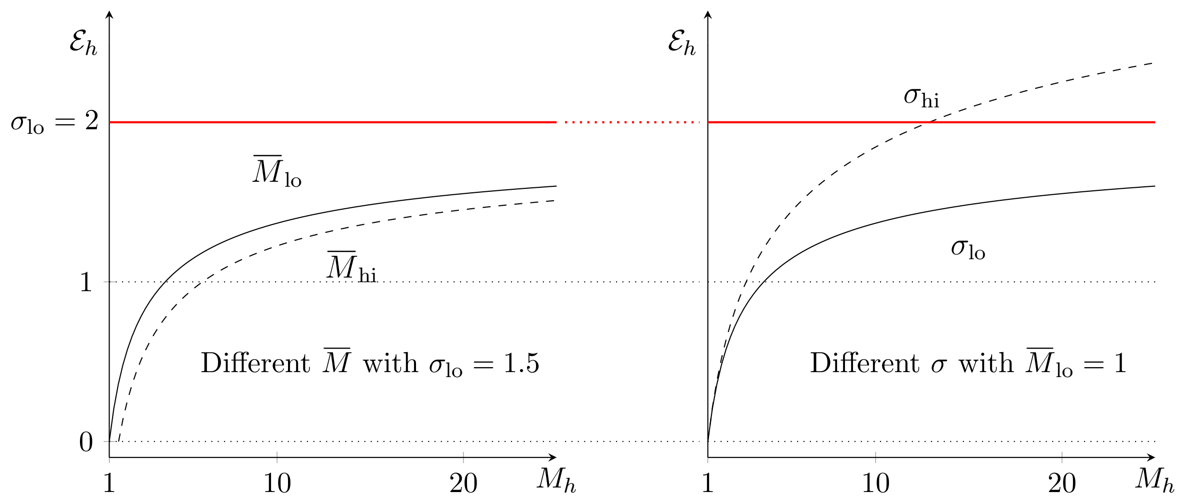

Figure 3. Elasticity as a function of the mass of firms in the industry M_h. The left panel shows the comparative statics of the consumer demand elasticity when we change $\overline{M}_h$. The right panel shows comparative statics with respect to σ_h.

with $\overline{M}_h$; when the product market space is large, the industry can accomodate more firms and the marginal effect of new entrants is small. The addition of one new parameter with respect to the standard model is crucial here to be able to determine both the average markup in an industry (equation (3.10)) and the elasticity of profits to entry (equation (3.11)).

To summarize, two forces in the model shape the cash flow risk of incumbent firms.[15] First, the dynamics of new firms entry and their response to aggregate fluctuations across industries depends on the supply elasticity of entrepreneurs, ζ_h, which maps into our measured exposure of Section 2.1. Second, demand elasticity, derived from consumer preferences, determines the response of firms profits to new firm entry, and both demand parameters (σ_h and $\overline{M}_h$) also map into their empirical counterpart η_h measured in Section 2.2. It is important to understand intuitively how both elasticities affect the risk of incumbent firms to an entry shock X_t: ζ_h answers the question: "how many firms enter the industry?" and η_h: "how much did incumbents lose in profit due to these new entrants?".

3.3.3 Aggregate Risk

New firm entry at the industry level is determined by the entrepreneurs first order condition (3.4) and depends on the aggregate factor X_t. To map the risk of industry entry into equilibrium asset prices it is necessary to understand how households perceive this risk. In other words we need to find the price of entry risk. The price of risk for a given shock is the price the representative agent is willing to pay for a standardized payoff ε, with mean zero and unit risk. Given a stochastic discount factor (SDF) S_t, the price of risk is defined

[15] A third force affects firm profits in this model. There are linkages across industries due to the Cobb-Douglas industry aggregator (see equation (3.2)). If one industry lowers its prices there will be some substitution effects from other industries. I evaluate the impact of such linkages in Appendix Section A.2.2 and conclude these effects are quantitatively small with respect to the effects within industry.

in the literature as:

$$rp_t(\varepsilon) = -\operatorname{cov}_t \frac{S_{t+1}}{S_t} \varepsilon_{t+1}.$$

Intuitively if S_{t+1} correlates positively with ε_{t+1} ($\partial_\varepsilon S > 0$), then the asset pays off in a state of high marginal utility, where the price of consumption is high. This leads to a higher price for the asset, also described as a negative price of risk. To capture how households perceive the risk of entry, we decompose its effects on each component of the SDF:

$$rp_t(\varepsilon) = -\frac{S_{t+1}}{S_t} \cdot \left(-\nu \cdot \frac{\partial \log C_{t+1}}{\partial \varepsilon_{t+1}} + (\nu - \gamma) \cdot \frac{\partial \log J_{t+1}}{\partial \varepsilon_{t+1}} \right) \tag{3.12}$$

We are interested in risk of entry, therefore we need to find how a shock to ε^X to the aggregate factor X affects both contemporaneous consumption C_t and the continuation utility J_t. In Appendix A.2 we show how contemporaneous consumption reacts negatively to an entry shock $\partial_{\varepsilon^X_{t+1}} C_{t+1} < 0$. Intuitively when the marginal productivity of entrepreneur, X_t, increases, resources are reallocated from the consumption good sector to the investment sector leading to a contemporaneous fall in consumption.[16] However, entry shocks affect the continuation utility positively, $\partial_{\varepsilon^X_{t+1}} J_{t+1} > 0$, since they expand the investment opportunity set of the economy in the future. Therefore the price of entry risk depends on these two concurring effects, and how much households evaluate them depends on the relation between their desire to smooth consumption across states (their risk aversion, γ) and their desire to smooth consumption across time (their elasticity of intertemporal substitution, ν^{-1}).[17]

To understand the exact mechanism behind the price of entry risk I decompose these two concurring effects. The effect of the entry shock on contemporaneous consumption is only driven by the first term in (3.12). If the asset pays off when consumption is low (state of high marginal utility) then its price is high and we say the price of risk is negative, $rp_t(\varepsilon) < 0$. How large it is quantitatively depends on the smoothing motives of the agent through the EIS, ν^{-1}. The price of risk is larger (more negative) when the agent has preferences for smooth consumption profile over time, in other words, low EIS (and large ν).

The sign of the price of risk due to the continuation utility component in (3.12) (the second part) depends on two forces: the agent's risk aversion and his smoothing motives. If $\nu - \gamma < 0$ then the contribution to the price of risk is positive. Since the continuation utility covaries positively with the shock, then the asset pays off in time where the continuation utility is high, leading to a low price for the asset, and a positive price of risk: $rp_t(\varepsilon) > 0$. In this case risk aversion is larger than the time-smoothing motives ($\gamma > \nu$) , leading to a positive contribution to the overall price of risk. The agent cares a lot about the risk of his continuation utility, which itself comoves positively with the shock ε^X. If $\nu - \gamma > 0$ then

[16] This is a standard result of comovement in the real business cycle model, see for example Christiano and Fitzgerald (1998).

[17] Details of the proof for the response of contemporaneous consumption and the continuation utility are in Appendix A.2. This mechanism is akin to the response of the stochastic discount factor to capital-embodied shocks (investment-specific technological change) in general equilibrium with an intensive margin of adjustment for investment. Papanikolaou (2011) shows that under some preference assumptions, the price of investment shocks is negative. This mechanism generates cross-sectional implications for firms, as it favors future "growth" opportunities and is detrimental to assets in place. See also Kogan et al. (2018) for an amplification of the mechanism.

the agent's smoothing motives are stronger than his risk aversion. In our context this leads to a more negative price of risk. To see exactly how it is easier to rewrite the price of risk from (3.12) as:

$$rp_t(\varepsilon) = \gamma \cdot \frac{S_{t+1}}{S_t} \cdot \frac{\partial \log J_{t+1}}{\partial \varepsilon_{t+1}} - \nu \cdot \frac{S_{t+1}}{S_t} \cdot \left(\underbrace{\frac{\partial \log J_{t+1}}{\partial \varepsilon_{t+1}}}_{>0} - \underbrace{\frac{\partial \log C_{t+1}}{\partial \varepsilon_{t+1}}}_{<0} \right)$$

So when smoothing motives are higher than risk aversion, the second term is larger and the agent is willing to pay a high price for an asset that pays when there is a shock with an opposite effect on contemporaneous consumption and continuation utility. We say the price of risk is negative, $rp_t(\varepsilon) < 0$.

Thus in the first case risk matters more, whereas in the second case smoothing motives are of more importance. The sign of $\nu - \gamma$ is tied in the literature for the agent's preferences for lotteries with early versus late resolution of uncertainty. When $\nu - \gamma < 0$ the agent has preferences for early resolution of uncertainty and when $\nu - \gamma < 0$ the agent has preferences for late resolution of uncertainty. The trade off is explained in detail in Weil (1990): early resolution lotteries are less risky for the same payoffs; however early resolution lotteries have movements of their certainty equivalent over time of larger amplitude. Hence the preference for early versus late hinges on the need for safety (risk aversion) and the stability of utility over time (smoothing motives).

I have presented preliminary empirical evidence in Table 2 that firms that are more exposed to the risk of entry tend to have higher average returns. I investigate this result thoroughly in the empirical Section 4 and confirm its robustness. For now, the result suggests that the price of entry risk is negative, and investors require a positive risk premium to hold assets exposed to this risk.

3.3.4 The Cross Section of Industry Risk Premia

After studying the partial equilibrium effects of entry on firms (Section 3.3.1 and 3.3.2) and the impact of the entry factor on the aggregate risk premium (Section 3.3.3), we are finally able to draw conclusions on the asset pricing implications of entry risk for the cross-section of returns across industries. Firms in different industries respond differently to aggregate shocks for two reasons: their entry margin differs, ζ, and the response of profits to entry also differs, η which depends on both parameters σ_h and $\overline{M}_h$.

There are two aggregate shocks in the model such that I can decompose the compensation for risk for a given firm into its loadings on both sources of risk multiplied by their respective price of risk. Linearizing the SDF around the non-stochastic steady state of the economy, I express this decomposition formally for a firm in industry h:[18]

$$\mathbf{E}_t \left\{ R^e_{h,t} \right\} \simeq \mathrm{rp}^A_t \, \mathrm{Cov}_t \left(\frac{v_{h,t+1} + \pi_{h,t+1}}{v_{h,t}}, \varepsilon^A_{t+1} \right) + \mathrm{rp}^X_t \, \mathrm{Cov}_t \left(\frac{v_{h,t+1} + \pi_{h,t+1}}{v_{h,t}}, \varepsilon^X_{t+1} \right). \quad (3.13)$$

The first component represents the compensation for carrying risk associated with aggregate productivity, A_t. This compensation is quantitatively small in practice and does

[18] I derive the approximation in Appendix A.2

not generate meaningful differences in risk premium across industries. This is a consequence of the equity risk premium puzzle; here the price of risk of aggregate productivity is approximately the product of risk aversion with the standard deviation of the shock. It is negligible for reasonable values: if we assume a fairly large risk aversion coefficient $\gamma = 10$, and a standard deviation of productivity of two percent, the compensation for risk is of the order of $\gamma\sigma_A^2 = 0.4\%$.

The second component is the key component of the model. Exposure to the aggregate entry factor matters for two reasons. First as we have argued there is significant heterogeneity in the response of profits to an aggregate shock to the productivity of entry, through both elasticities ζ and η. Second the price of risk can not only be negative as I described in Section 3.3.3 above, but also it can be quantitatively large. A positive shock to the productivity of entry, X_t, leads to an increase in the risk free rate, due to substitution effects, which decreases all valuations in the economy. The value of firms that are exposed to entry risk declines at times when the marginal utility of wealth is very high leading to significant differences in the compensation for risk. We confirm this intuition in our estimation in Section 5, showing how the compensation for entry risk is indeed large even for small values of risk aversion.

In this Section, I have developed an asset pricing model with heterogeneous industries and entry risk. The model introduces two new ingredients that are borne out in the data. First, I have introduced an inelastic entry margin such that different industries have different elasticities, ζ with respect to the aggregate entry factor X_t. Second, I have departed from the standard Dixit-Stiglitz framework of constant elasticity of substitution to introduce consumer demand elasticities that depend on the product market structure of an industry. Thus the effect of new firms on incumbents' profits differ across industries depending on their market structure, summarized by the statistics η. In the next section, I turn to the data and to find direct evidence of our predictions along these two dimensions of industries' exposure to risk, before we quantitatively assess the performance of the model in Section 5.

4 Empirical Evidence

In Section 2, I introduced two measures of key industry characteristics related to entry risk — industry entry elasticity, ζ and profit elasticity, η. Starting from these two measures I examine whether firms that are more exposed to entry risk also have higher average returns.

4.1 Stock-Level Data

I obtain stock return data from the Center for Research in Security Prices (CRSP monthly file) and accounting data from COMPUSTAT. My sample includes all firms with ordinary stocks — that is, with CRSP share codes of 10 or 11 — traded on the Amex, NASDAQ, or NYSE between 1992 (the first year where I start my analysis) and 2017. I use the four-digit NAICS code from COMPUSTAT if available, and the four-digit NAICS code from CRSP otherwise; I exclude firms in regulated industries, with NAICS two-digit code in utilities (22), finance and insurance (52), or public administration (92). Over the 1992 to 2017 sample period, this leaves me with a sample of 1,284,101 stock-month observations for 17,330 distinct stocks.

I retrieve data on stock characteristics from the CRSP-COMPUSTAT merged database. Size is the average portfolio market capitalization over the sample period converted into 2013 constant billions dollars. Cash flows at the quarterly frequency are defined following Rajan and Zingales (1998), as earnings before interest, taxes, depreciation and amortization from the COMPUSTAT files (item `EBITDA`) plus decreases in inventories (item `INVT`), decreases in receivables (item `RECT`) and increases in payables (item `AP`), all scaled by assets (item `AT`). Book-to-market is defined as book value of equity (item `CEQ`) divided by market value of equity (item `CSHO` $\times$ item `PRCC_F`). Book leverage is total debt (item `DLC` + item `DLTT`) divided by the sum of total debt and book value of equity. Return on assets (ROA) is defined as operating income after depreciation and amortization (item `OIBDP` − item `DP`) divided by total assets. Invesment is the investment ratio of capital expenditures (item `CAPX`) divided by property, plants, and equipment (item `PPENT`). Finally I measure markups at the four-digit NAICS level using the methodology developed by Loecker and Eeckhout (2017) on the set of firms in the CRSP-COMPUSTAT sample; I leave details of the construction of the markup measure in Appendix B.1.

I first form equally-weighted industry portfolios based on the quintiles of measured exposure to the aggregate entry factor, ζ_h in Panel A of Table 2. While size, leverage, investment, and average markups are stable with respect to ζ_h, I find that the more exposed industries (high ζ_h) have lower book-to-market, lower profitability, more volatile markups and higher average returns.

I also form equally-weighted industry portfolios based on the quintiles of measured profit elasticity to industry entry, η_h in Panel B of Table 2. I find a pattern similar to Panel A across quintiles of industries: while size, leverage, investment, and average markups are stable with respect to η_h, I find that the more exposed industries (more negative η_h) have lower book-to-market, lower profitability, more volatile markups and higher average returns.

4.2 Portfolio Analysis

A potential concern with the preliminary results from Table 2 is that the difference in average returns across industry portfolios reflects the differential composition of the industries or their exposure to risk factors, irrespective of their actual exposure to entry risk. To address this concern, I estimate abnormal excess returns as the residuals of the three-factor and five-factor model of Fama and French (2015), in which standard errors are adjusted using the Newey-West procedure with 12 lags. I confirm that the risk premium we capture is not subsumed by loadings on classic risk factors, namely, the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), the profitability factor (robust minus weak), and the investment factor (conservative minus aggressive) —all obtained from Kenneth French's website.

4.2.1 Portfolios with Respect the Dynamics of Industry Entry: ζ

As evidenced in Table 3, I find that the long-short portfolio (that is, long industries with a large exposure ζ_h with respect to the entry factor and short industries with a small exposure) has an alpha with respect to the five-factor model that is 8.2% annually

(t-statistic = 4.0). Importantly, when portfolio returns are value-weighted, the long-short alpha is still statistically significant, at 8.0% annually (t-statistic = 4.65). Results with respect to the three-factor model are slightly weaker though still quantitatively significant, 3.7% (marginally statistically significant with t-statistic = 1.62) for the equally-weighted portfolio and 4.9% (t-statistic = 2.65) for the value-weighted portfolio. The excess returns on the value-weighted portfolio underscore that shocks to the aggregate entry factor matter for investors' wealth.

4.2.2 Portfolios with Respect the Elasticity of Firm Profit: η

In Table 4, I repeat the previous exercise and sort industries along quintiles of the elasticity of profits to industry entry, η_h. I find that portfolios in industries with risky profits, low η_h, have higher alpha than portfolios in high η_h, and the decline in portfolio alpha is monotonous along quintiles of η_h. In Panel A of Table 4, I show that the long-short equally-weighted portfolio along η_h characteristics has an three-factor alpha of 3.47% annually (t-statistic = 2.2); the value-weighted long short portfolio has an alpha of 4.67% (t-statistic = 4.1). The results are unchanged when we consider the five-factor model in Panel B where the long-short portfolio earns alpha of 4.75% equally weighted and 3.6% both strongly statistically significants.

4.2.3 Portfolios along both Dimensions of Entry Risk: ζ and η

Each of the elasticity, ζ_h or η_h, capture a different dimension of entry risk. The industry entry elasticity ζ informs us on the covariance of an industry entry dynamics with the aggregate entry factor X_t, while the profit elasticity η measures the real threat of competition for firms. Even though the analysis separates the role of both elasticities, they jointly affect equilibrium asset returns. Let us take two extreme cases to illustrate how their role on asset prices is intertwined. First consider an industry that has high aggregate loadings ζ but where the risk of competition is null. Firms in this industry are not exposed to entry risk, as their profits are independent of new firm entry, while there still might be fluctuations in entry driven by aggregate factors. The other industry represents the polar opposite case: incumbent firms in this industry have a large exposure of their profits to new entrants, yet the dynamics of entry has no correlation with the aggregate factor. While cash flows are risky, the risk will not be priced and firms in the industry will not receive any compensation for entry risk.

I test this proposition in Table 5 (and Table 6), by forming industry portfolios sorted by terciles of both elasticities ζ_h and η_h. I find that for firms in industries that have a high exposure to the aggregate factor, high ζ_h, the elasticity of firm profits matters. In columns (1), (2), and (3) of Table 5, I find that portfolios alpha are decreasing with respect to profit risk as measured by the elasticity η_h. Portfolios with low η_h have higher annual three-factor alpha (5.7%) than firms with higher η_h (0.8%). This pattern is also present for value-weighted portfolios, as well as for five-factor alpha. The long-short portfolio, in Table 6, that goes long low η_h industries and short high η_h industries for the most exposed industries, high ζ_h has a three-factor alpha of 4.85% (t-statistic = 1.8) and a five-factor alpha of 9.3% (t-statistic = 3.7).

In the last three columns of Table 5, I consider whether the elasticity of industry profits matters for equity returns when these industries have little exposure to the aggregate entry factor, if they are in the lowest tercile of ζ_h. I find no significant differences in returns (or risk adjusted alpha) with respect to η_h elasticity, suggesting that exposure to ζ_h is necessary for firms to receive a compensation for entry risk and that profit elasticity alone is not sufficient. In column (3) of Table 6, I show the three-factor alpha of a long-short portfolio of low ζ_h industries that goes long low η_h industries and short high η_h is -2.87% and not statistically significant (t-statistic = 1.3).

Finally, I present results that support the necessity of profit elasticity η_h. In Table 6, I consider three double-sorted portfolios that are long high terciles of ζ_h elasticity and short low terciles of ζ_h, conditionally on terciles of the elasticity η_h. As expected, given the results highlighted above, I find the returns of this portfolio to be high whenever firms' profits are exposed to new entrants, that is when η_h is low. The three-factor alpha of this portfolio is 5.6% (t-statistic = 1.56) and the five-factor alpha is 8.9% (t-statistic = 2.8). However in columns (5) and (6), the elasticity of profits to entry are smaller and I find that sorting industries based on their aggregate entry elasticity ζ_h, does not generate significant differences , statistically or economically, in returns; the three-factor alphas are 3% (t-statistic = 1.6) and -2.1% (t-statistic = 1.1) for the middle and highest tercile of η_h respectively. Even though there are differences in the exposure of industries with respect to the entry factor, if firm profits are not affected by entry, these firms are not exposed to entry risk and do not receive any premium.

4.3 Relation to the literature.

Recent work on the subject of industrial organization and asset pricing has shown that the market structure of industries predicts stock returns. Bustamante and Donangelo (2017) find that more concentrated industries tend to have higher cash flow risk and thus higher average returns — the spread in abnormal returns (annualized) from the three-factor model range from 1.5% to 1.9%. Likewise, Corhay et al. (2015) note that when average markups are higher, they are also more sensitive to entry, translating into higher risk for firms.

Both analyses are centered around cash flow risk. They correspond to the elasticity of firm profits to entry η_h that I measure and introduce in the model above. A crucial aspect of the model described in Section 3 is to highlight the complementarity of the two sources of risk. Industries are risky because the dynamics of new entrants correlate with the aggregate entry factor, the elasticity ζ_h. But the risk only materializes if the new entrants pose a threat to the incumbents' cash flow, the elasticity η_h. In Section 2, I present a direct way of measuring the elasticity η_h; however, different measures like the ones used in Bustamante and Donangelo (2015) and Corhay et al. (2015), which account for cash flow risk, should also interact with the aggregate elasticity ζ_h. Moreover, these measures are widely used in the industrial organization literature and it is important to reconcile them with my findings.

First, I highlight similarities of the cash flow risk measures in Table C.11. I present summary statistics of the measures used in Bustamante and Donangelo (2017) and Corhay et al. (2015) across three terciles of industries based on the profit elasticity η_h. All measures of risk concur such that industries with high markups or high concentration also have a very negative profit elasticity. In Tables C.12 and C.13, I sort industries based on their exposure to the entry factor, ζ_h, and the different measures of cash flow risk. The two tables reproduce the double-sort exercise from Tables 5 and 6. I consider three alternative measures of cash flow risk: first, in panel B, I use the concentration ratio of industries from the Census of Manufactures; in panel C, I consider the Herfindahl-Hirschman index from the Census; in panel C, I sort industries based on their levels of markup. Panel A reproduces my original results based on the profit elasticity η_h for easy comparison. Zooming in on panel B, I find that in industries with aggregate elasticity ζ_h, firms in more concentrated industries tend to have higher returns. However, moving towards industries with low aggregate elasticity, differences in cash flow risk does not materialize into significant differences in average returns. This pattern is robust to the different proxies for cash flow risk such as Herfindahl (panel C) and markups (panel D). Overall these results illustrate the great complementarity of my work with the existing literature and stress the necessity of understanding both aggregate risk, through ζ_h, as well as cash flow risk, through η_h, to fully account for the cross-section of industry returns.

4.4 Robustness

I assess the robustness of these findings in several ways. First I consider a different way of measuring entry, then I consider extending the sample back to 1970 and finally I formally test for the market price of risk using factor mimicking portfolios.

Measuring Firm Entry. I measure firm entry using all establishments rather than new firms. The data from the QCEW does not distinguish whether an establishment is a standalone firm or part of a multiplant firm. Thus using an establishment's entry rather than a firm's entry, I measure both entry at the extensive margin from new firms as well as entry at the intensive margin from existing firms opening new establishments. While there is no question that a new firm will increase the number of competitors, the issue with existing firms opening new establishments is more subtle, since opening a new establishment might not necessarily increase competition. For example, if Walmart opens a new establishment in a market where it wasn't present before (for example in the city of Chicago after 2011), then the profit of the Walmart Corporation will increase as Walmart itself will not be affected by its own competition. However other grocery stores in the market of Chicago grocery stores (Jewel Osco, Whole Foods, ...) will be negatively affected by the competition and their profits will decline.

As a robustness exercise to alleviate concerns regarding my measure of entry from the QCEW, I consider restricting entry to small firms in the QCEW data that are more likely to capture entry on new firms rather than expansion of existing firms. I have re-estimated my econometric model limited to entry of small establishments (below 50 employees), and I have added the Tables in the Appendix for robustness (see C.2 and C.3). In Appendix Table C.2 I find that an equally-weighted industry portfolio that goes long the highest quintile of the elasticity of industry entry to the aggregate factor ζ, and short the lowest quintile, earns a five-factor alpha of 6.7% (t-statistic = 4.2). An identical portfolio, but value weighted, earns a five-factor alpha of 6.5% (t-statistic = 3.1), confirming that the effects are relevant for all types of firms. In Appendix Table C.3, I consider double sorted portfolios on ζ and then η to confirm the robustness of our main Table 5. I find that only firms in industries with high elasticity ζ and relatively low elasticity η receive statistically and quantitatively significant risk compensation, confirming the essential role of both elasticities.

Finally it has been shown that establishment entry is a conservative measure of the impact of new products on an industry market structure. Recent work with disaggregated data shows substantial product creation within firms as has been shown in Bernard et al. (2010) and Broda and Weinstein (2010).[19] Thus measuring establishments rather than actual entry into a new product market would only introduce downward bias in our estimates of ζ and η leading us to find no relation between industry elasticities and average returns of industry portfolios.

Unlevered Returns. D'Acunto et al. (2018) show how firms with relatively more flexible prices also have higher leverage. Given the link between the frequency of price adjustment and the dynamics on product markets, a mechanical variation in leverage across industries with different elasticities could account for the patterns of average returns described above in Tables 3, 4, and 5. In Appendix Tables C.4, C.5, and C.6, I replicate these three tables for unlevered returns at the firm level and confirm that my results are robust to heterogeneous leverage.[20]

Extending the Sample. First I consider an extended time period for external validity. Even though the micro-level data on entry only starts in 1992, I take my estimates and assign retroactively to each industry their entry elasticity measured during the 1992-2017 period. The results in Appendix Table Table C.7 show the difference in average returns along ζ are unchanged quantitatively and qualitatively. I reproduce the exercise assigning profit elasticities η retroactively in Table C.8. I am able to confirm that the results based on profit elasticities are also unchanged. One takeaway of this set of robustness tables, beyond the external validity, is the persistence in industry structure such that measuring elasticities in one part of the sample extends to another part.

Estimating the Market Price of Risk. To complement the portfolio analysis, I also present evidence for the price of entry risk using a more direct estimation method. I estimate a linear approximation of the SDF defined in the model (equation (3.13)) which loads on the two factors, the aggregate productivity A_t and the aggregate entry X_t:

$$S = b_0 - b_A \varepsilon^A - b_X \varepsilon^X. \tag{4.1}$$

Following Cochrane (2005), I use two factor mimicking portfolios, the market for the aggregate productivity shock and a long-short portfolio on the entry elasticity for shocks to the aggregate entry factor. For the latter I use both portfolios along the entry elasticity ζ

[19] Bernard et al. (2010) use plant-level data at a fine level of industry disaggregation (five-digit SIC code) to investigate the dynamics of product creation within firms. Their study shows 94% of new products are created within existing firms. At a finer level, Broda and Weinstein (2010) use barcode data and confirm the role of product creation for existing firms and find the market share of new products is four times that of newly created firms.

[20] Table 2 show that leverage present little variation in leverage across industry groups; moreover D'Acunto et al. (2018), find no effect of industry variables, concentration and price-costs margins, on firm leverage.

and the profit elasticity η. Details of the generalized method of moments estimation is in Appendix Section B.2.

I present the results in Appendix Tables C.9 and C.10. Appendix Table C.9 presents results for a factor mimicking portfolio that is long-short on ζ sorted industries; I find that the price of risk is quantitatively and statistically significant. Its magnitude ranges from 0.37 to 0.56 and is comparable to the market risk premium. In Appendix Table C.10, I replicate the estimation with a factor mimicking portfolio that is long-short on η sorted industries; likewise I find that the price of risk is significant.

5 Estimation of the Model

I now turn to the quantitative estimation of the model. In the estimation, the goal is to assess whether the mechanisms described in the theoretical framework (Section 3.3) can account quantitatively for the cross-sectional differences in industry returns documented in the empirical Section 4.

To map the model to the data while keeping the estimation computationally feasible, it is necessary to reduce the number of industries down from 303. I choose the smallest number of industries that are rich enough to account for the two layers of heterogeneity of the model (ζ_h and η_h) while still being tractable. Thus, I settle on four sectors that represent all of 303 industries from the riskiest to the least risky: high-ζ_h/low-η_h, low-ζ_h/low-η_h, high-ζ_h/zero-η_h, low-ζ_h/zero-η_h. To find an empirical counterpart to each of these four large sectors, I aggregate all the industries based on their individual aggregate elasticity (ζ_h) and profit elasticity (η_h). After forming the four sectors, I estimate all of the moments to which the model is matched. The targeted statistics are in panel A of the estimation Table 9, while other untargeted moments are in Table 8.

5.1 Calibrated Parameters

Table 7 lists the calibrated parameters. These parameters are harder to identify from the cross-sectional data analysis and I choose some based on targeted moments and others based on the existing literature. To calibrate household preferences I take a subjective discount factor at monthly frequency of 0.998 as in Bansal and Yaron (2004). I choose a value of the EIS of $\nu^{-1} = 0.5$ that is consistent with the micro-level estimates of Vissing-Jorgensen (2002) and I choose a value for the coefficient of risk aversion of $\gamma = 3$ that is in the range of plausible risk parameters estimated in the literature.

On the production side, the parameters governing the dynamics of technology shocks are standard. I calibrate the volatility of the neutral productivity shocks $\sigma_A = 2$ percent to match the volatility of consumption with a persistence parameter of $\rho_A = 0.99$; the growth rate of aggregate productivity is set to $\mu_A = 1$ since the model is stationary and does not allow for growth.[21] I calibrate shocks to the entry factor based on the average volatility of

[21] As in Bilbiie et al. (2012), I assume a zero growth rate. In my model as in most models of innovation based theory of growth, the growth rate of the economy is a function of the incentives of firms to innovate or of new firms to enter. These incentives are determined in my model by the elasticity of consumers' demand curve through the incumbents' markup. This elasticity is non-stationary as the economy expands the mass of varieties in an industry expands. The non-stationarity of markup dynamics based on industry age is an

entry across industries such that $\sigma_X = 10\%$ and I estimate directly the persistence of the entry factor in the data to $\rho_X = 0.8$ (note that I only recover a normalized X_t factor which is why I use ex-post volatility to calibrate its volatility).

5.2 Estimated Parameters and Choice of Moments

We estimate all of the industry specific parameters for each of the four industries. Two parameters $(\sigma_h, \overline{M}_h)$ govern the shape of the demand elasticity and the behavior of markups. The two other parameters control the shape of the entry margin through the cost function of entrepreneurs $(f_{e,h}, \zeta_h)$. Last, the death rate controls the level of turnover in a given sector such that the set of estimated parameters Θ is:

$$\Theta := \left\{\sigma_h, \overline{M}_h, f_{e,h}, \zeta_h, \delta_h\right\}_{h=1\dots4}$$

We choose these parameters to estimate because the theory predicts that they govern the dynamics of asset prices through the market structure of the industries There are 20 parameters to be estimated, for which I use 24 identifying moments, or six moments for each of the industry. First I use the industry level elasticities measured in Section 2: the entry elasticity to X_t, ζ and the profit elasticity to entry η. I include the average level of markups at the industry level, which gives information about the steady state product market structure. To match the cross-section of risk across sectors I include average excess returns. Last, I consider both entry and exit rates across sectors as the last eight additional moments.

5.3 Estimation Results

Identification. I use standard methods to estimate the model and in Table 9, I present the list of targeted moments, their fit in the model, and the parameter estimates. First note that the model is overidentified given that there are only 20 parameters for 24 moments.

Non-linearities and the interplay between parameters play a substantial role, thus it is hard to give a direct interpretation of single moments identifying single parameters. However the difference between industries is telling. Industries with high aggregate elasticity ζ_h not only have a differ supply elasticity but also a smaller fixed cost of entry, $f_{e,h}$. From equation (3.9), the fixed cost of entry enters the equilibrium entry rate, thus higher value of ζ_h lead to smaller values of $f_{e,h}$ for similar entry rates. The profit elasticity across industries gives us some insight on the key demand parameters. The long run demand elasticity σ_h is between 2.4 (least risky industry) and 6.2 in line with the estimates commonly accepted of Broda and Weinstein (2006). Demand elasticity is relatively higher for sectors with large cash flow risk (negative η_h). The exogenous death rate δ_h is overdetermined: the model is stationary and in equilibrium the long run entry and exit rates have to be equal. Moreover the entry/exit rate depends on the dynamics of entry through ζ_h; my estimates of δ_h are not far from their empirical counterpart, they show larger standard errors than the other parameters.

Non Targeted Moments. I also evaluate the model with respect to non targeted moments. I evaluate the model implications for the volatility of entry at the industry level

interesting feature of the model in itself, however it falls outside of the scope of this paper.

and for other aggregate moments. I present the results in Table 8. First I show that the volatility of the entry rate across industries does not match the data perfectly. Industries with higher aggregate entry elasticity (high-ζ_h) have higher volatility than their empirical counterpart. On the other hand industries with low entry elasticity have lower volatility than in the data. Thus the difference of the volatility in the entry rate between high and low-ζ industries is much starker in the model than in the data. In my model entry is only driven by changes in the productivity of entry; many other forces, such as idiosyncratic risk, affect the entry margin, which also drives entry at the industry level without affecting stock returns.

It is important to check that the model does not have implications for aggregate moments that clash strongly with the data. The aggregate dynamics are mostly determined by calibrated parameters which are all chosen to be standard and from the literature. The second part of Table 8 shows how the model matches the average risk-free rate and its volatility. Moreover the model is able to match the standard deviation of consumption growth, which is mostly driven by aggregate productivity. Overall, the model shows that while it has rich implications for the cross-section of industries, it matches standard macro moments.

5.4 Evaluating the Mechanism Quantitatively

In the theoretical framework I showed how both elasticities ζ and η affect asset prices through their impact on the dynamics of firms' cash flows. Even though I detail the effect on the discount factor of aggregate entry, it is hard to directly evaluate the quantitative relevance of a partial equilibrium mechanism on cash flows once in general equilibrium. And while the SMM estimation gives an overview of the overall fit of the model as a whole, it is useful to focus on the more quantitative aspects of the mechanisms.

First let us take the elasticity of industry entry to aggregate factors, ζ. The model allows us to answer the following question: "How much compensation for risk do investors receive for a unit exposure to the risk of industry entry ζ?" In the data, one standard deviation increase in ζ_h, keeping the cash flow risk η_h constant, goes with average returns that are 1.8% higher, leading to a sensitivity that is around 4% on average.[22] In the model the elasticity is 5.8% on average.[23] The model exhibits a greater sensitivity of returns for higher values of cash flow risk highlighting the important complementarity betweeb the two elasticities η_h and ζ_h and echoing the results of Section 4.2.3 and the double-sort Table 5. The model exhibits a larger sensitivity than the data because it is not able to match sectors with very small elasticity of entry to the aggregate entry factor due to the strong non-linarities that arise from the first order condition in equation (3.4). I also evaluate the mechanism of the second core mechanism of the model: the cash flow risk. The model is able to match the profit elasticities perfectly, thus any discrepancies of the sensitivity of returns to η_h must stem from average returns. The sensitivity in the model is higher than in the data for high-ζ_h sectors, but lower in small-ζ_h sectors, again confirming the results

[22] For negative η_h sectors, the difference in elasticity is 0.4 and the difference in returns is 1.7%, the sensitivity is 4.1%. For sectors with small η_h the sensitivity is $(7.9\% - 4.9\%)/(0.6 + 0.1) \simeq 4.3\%$.

[23] For negative η_h sectors the sensitivity is $(9.5\% - 7\%)/0.325 \simeq 7.7\%$ and for small η_h sectors it is $(7.2\% - 5.2\%)/0.51 \simeq 3.9\%$.

of the double-sorted tables: the effect of cash-flow risk is strongest in industries exposed to aggregate entry.[24] On average over all sectors, the sensitivity of returns to the profit elasticity is very close in the model and in the data (33% in the model and 34% in the data).

From these two exercises I conclude that the model is quantitatively relevant. Both partial equilibrium mechanisms, the exposure of industry entry, ζ and the profit elasticity, η do generate significant differences in expected returns across industries for reasonable changes in industry structure. This evidence suggests a simple neoclassical growth model with imperfect competition can link asset prices with important industry characteristics such as innovation and product market structure. Not only does my model replicates key industry price and quantity moments but it also sheds light on the mechanism at play for this margin of investment: the extensive margin. Prices are informative not only about industry risk, but also about the incentives to innovate across industries. To confirm these theoretical findings, I conduct an empirical analysis of the link between these two key industry statistics (ζ and η) and asset prices.

6 Conclusion

In this paper, I introduced a general equilibrium model with heterogeneous industries, imperfect competition, and shocks to the aggregate cost of entry. Shocks to entry affect the monopolistic structure of industries differently depending on two elasticities: the elasticity of industry entry to aggregate fluctuation (ζ) and the elasticity of profits to industry entry (η). I identify the impact of shocks using asset prices. In industries with high elasticities (either ζ and η), changes in entry affect firm value significantly. I show this extensive margin of adjustment has a limited effect on industries with low elasticities.

I test the model using industry portfolios and confirm the crucial role of the two industry elasticities for equity returns. Industries with high entry elasticity earn returns that are 3.4% higher annually than industries with low elasticity and industries with high profit elasticity earn returns that are 2.4% higher annually than industries with low elasticity. I confirm that both elasticities are necessary and contribute together to the risk of entry. Finally I present evidence that the price of risk is negative, and after a shock to entry, the marginal utility of consumption increases.

The model is able to match the data quantitatively and emphasize the role of both elasticities for understanding entry risk. My results shed light on the link between industry organization and aggregate fluctuations. Macroeconomics shocks impact heterogeneous industries in different ways. Understanding the cross section of industry returns contributes to our understanding of how aggregate shocks percolate the economy. To this end, the use of financial data is invaluable, because it captures some of the crucial heterogeneity in the real economy.

[24] The sensitivity in the model for high-ζ_h is $(9.4\% - 7.3\%)/(0.047 - 0.002) \simeq 43\%$ and in the data it is $(9.6\% - 7.9\%)/(0.047 + 0.004) \simeq 33\%$. For low-$\zeta_h$ sectors the sensitivity in the model is $(7\% - 5.2\%)\%/(0.076 - 0) = 23\%$ and in the data $(7.9\% - 4.9\%)/(0.076 + 0.007) \simeq 36\%$

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Tables

Table 2

Summary Statistics of Industries Across Elasticity Groups

	Panel A: Summary Statistics across Elasticity Groups, ζ				
	High ζ_h – more risky	4	3	2	Low ζ_h – less risky
Firm level characteristics					
Size(bn)	3.32	2.38	2.34	2.15	2.29
Book to Market	0.682	0.828	0.874	1.08	1.11
Book Leverage	0.157	0.191	0.232	0.286	0.271
ROA	−0.121	0.0183	0.0498	0.0294	0.0696
Investment	0.178	0.147	0.138	0.16	0.183
Markups					
Markups Level	0.216	0.248	0.373	0.344	0.318
Markups Volatility	0.322	0.169	0.177	0.187	0.147
Industry Returns					
Mean excess returns (%)	15.1	13.4	11.4	11.5	9.25
Sharpe ratio	0.536	0.556	0.566	0.581	0.442
Covariance of Returns (%) with X_t (β^X)	−5.16	1.42	1.74	−4.37	−7.49
Industry Response to the Entry Factor					
Elasticity of Industry Entry to X_t	0.701	0.397	0.22	0.124	−0.279
Factor Loadings: ζ	18.7	9.37	5.82	1.24	−7.38

	Panel B: Summary Statistics across Elasticity Groups, η				
	Low η_h – more risky	2	3	4	High η_h – less risky
Firm level characteristics					
Size(bn)	2.09	2.69	2.78	3.34	1.84
Book to Market	0.939	0.727	0.811	0.995	1.04
Book Leverage	0.232	0.186	0.181	0.277	0.246
ROA	−0.0278	−0.0549	0.0151	0.0324	0.0659
Investment	0.156	0.21	0.163	0.145	0.137
Markup					
Markups Level	0.376	0.15	0.329	0.357	0.283
Markups Volatility	0.201	0.282	0.218	0.191	0.125
Industry Returns					
Mean excess returns (%)	12.5	13.4	13.1	11	10.2
Sharpe ratio	0.612	0.513	0.508	0.531	0.511
Covariance of Returns (%) with X_t (β^X)	−3.78	−4.29	−7.95	2.91	−3
Industry Response to Entry					
Elasticity of Industry Entry to X_t	0.218	0.337	0.457	0.186	0.0506
Elasticity of profits to industry entry, η	−7.96	−3.48	−1.01	1.11	10.8

The table reports summary statistics for firms in different 4 digits industries. I sort industries based on my measure of industry entry elasticity to aggregate entry ζ_h and also the elasticity of cash-flows to industry entry η_h as measured in Section 2.
Size is market equity in billions of dollars; Book-to-market is the ratio of book value to market value; Leverage is defined as the ratio of total debt to book value; ROA measures earnings before interests and depreciation minus inventories scaled by the total value of assets; Investment is defined as the ratio of capital expenditure to asset. Markups are measured as in Loecker and Eeckhout (2017). Returns are multiplied by 1200 for comparison with annual returns. The elasticity of industry entry to X_t is measured as the regression coefficient of industry entry to the aggregate entry shock X_t.

Table 3

Portfolios Sorted on the Elasticity of Industry Entry to Aggregate Entry: ζ

Portfolio quintiles	High ζ_h	4	3	2	Low ζ_h	Hi–Lo	High ζ_h	4	3	2	Low ζ_h	Hi–Lo
	Fama-French 3 Factor Model: Equally Weighted						Fama-French 3 Factor Model: Value Weighted					
α	5.53**	3.35**	1.69	0.99	−1.62	7.16***	3.69***	0.87	0.40	−1.59	−1.10	4.79**
	(2.61)	(1.54)	(1.54)	(1.72)	(1.54)	(2.69)	(1.14)	(1.31)	(1.14)	(1.2)	(1.12)	(1.94)
β^{MKT}	1.143	1.143	0.983	1.002	1.091	0.052	0.980	1.200	0.823	1.008	0.954	0.025
β^{HML}	−0.594	−0.203	0.146	0.411	0.303	−0.897	−0.487	−0.407	0.184	0.360	0.073	−0.560
β^{SMB}	1.223	0.941	0.825	0.771	0.794	0.429	−0.042	0.113	0.021	0.116	−0.029	−0.013
	Fama-French 5 Factor Model: Equally Weighted						Fama-French 5 Factor Model: Value Weighted					
α	10.43***	6.44***	2.28	0.95	−0.86	11.29***	3.82***	3.19**	−1.40	−3.39***	−2.63**	6.45***
	(2.66)	(2.05)	(1.9)	(1.94)	(1.96)	(2.33)	(1.23)	(1.41)	(1.26)	(1.18)	(1.14)	(2.01)
β^{MKT}	0.976	1.034	0.965	0.995	1.059	−0.083	0.977	1.114	0.897	1.070	1.007	−0.030
β^{HML}	−0.368	−0.040	0.165	0.456	0.376	−0.744	−0.489	−0.253	0.021	0.273	0.001	−0.490
β^{SMB}	0.962	0.789	0.789	0.801	0.777	0.185	−0.053	0.019	0.067	0.209	0.051	−0.105
β^{RMW}	−0.827	−0.493	−0.110	0.074	−0.074	−0.753	−0.033	−0.322	0.187	0.297	0.254	−0.287
β^{CMA}	−0.063	−0.102	0.016	−0.145	−0.129	0.066	0.022	−0.179	0.274	0.037	0.026	−0.004

Table 3 presents excess returns (α) over a three and a five factor Fama-French model of industry portfolios sorted by quintiles of their elasticity ζ of industry entry to aggregate entry shocks.

I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), and for five factors the additional profitability (robust minus weak) and investment factor (conservative minus aggressive) all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns. Portfolios returns are either equally weighted (columns (1) to (6)) or value weighted (columns (7) to (12)). Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 1992 to 2017.

Table 4

Portfolios Sorted on the Firm Cash-Flow Elasticity to Entry: η

Portfolio quintiles	Low η_h	4	3	2	High η_h	Hi–Lo	Low η_h	4	3	2	High η_h	Hi–Lo
	Fama-French 3 Factor Model: Equally Weighted						Fama-French 3 Factor Model: Value Weighted					
α	2.91^{*}	3.24	3.54^{*}	0.24	−0.35	-3.26^{***}	1.61	1.24	−0.55	0.20	−0.91	-2.52^{**}
	(1.7)	(2.02)	(2.05)	(1.64)	(1.34)	(1.17)	(1.15)	(1.13)	(1.25)	(1.01)	(1.02)	(1.14)
β^{MKT}	0.988	1.156	1.132	1.082	1.018	0.031	0.906	1.010	1.138	0.914	0.995	0.089
β^{HML}	0.094	−0.350	−0.414	0.320	0.368	0.274	0.003	−0.282	−0.445	0.116	0.080	0.078
β^{SMB}	0.852	1.132	1.007	0.747	0.783	−0.068	0.074	−0.016	0.038	0.019	0.042	−0.032
	Fama-French 5 Factor Model: Equally Weighted						Fama-French 5 Factor Model: Value Weighted					
α	4.04^{*}	6.56^{***}	7.59^{***}	1.01	−0.31	-4.35^{***}	0.00	1.19	1.29	−0.47	-2.59^{**}	-2.59^{*}
	(2.09)	(2.46)	(2.32)	(1.94)	(1.7)	(1.27)	(1.16)	(1.21)	(1.05)	(1.02)	(0.988)	(1.37)
β^{MKT}	0.944	1.037	0.985	1.053	1.011	0.068	0.968	1.015	1.064	0.941	1.057	0.089
β^{HML}	0.178	−0.175	−0.181	0.376	0.408	0.231	−0.112	−0.301	−0.299	0.061	−0.016	0.095
β^{SMB}	0.808	0.948	0.799	0.717	0.812	0.004	0.140	−0.025	−0.025	0.040	0.129	−0.011
β^{RMW}	−0.153	−0.569	−0.660	−0.104	0.060	0.213	0.226	−0.017	−0.233	0.081	0.275	0.049
β^{CMA}	−0.103	−0.066	−0.148	−0.069	−0.131	−0.028	0.134	0.054	−0.205	0.081	0.061	−0.072

Table 4 presents excess returns (α) over a three and a five factor Fama-French model of industry portfolios sorted by quintiles of their elasticity η of cash flow to industry entry. I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), and for five factors the additional profitability (robust minus weak) and investment factor (conservative minus aggressive) all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns. Portfolios returns are either equally weighted (columns (1) to (6)) or value weighted (columns (7) to (12)). Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 1992 to 2017.

Table 5

Portfolios based on both ζ_h elasticity and η_h elasticity

Portfolio - ζ_h	High ζ_h			Mid ζ_h			Low ζ_h		
Portfolio - η_h	Low	Mid	High	Low	Mid	High	Low	Mid	High
	Fama-French 3 Factor Model: Equally Weighted								
α	5.563**	3.237*	0.864	1.597	1.249	0.277	0.365	0.688	2.934
	(2.64)	(1.94)	(1.64)	(1.62)	(1.75)	(1.51)	(2.73)	(1.61)	(1.82)
β^{MKT}	1.2	1.14	0.875	0.974	0.925	1.01	1.01	1.02	0.836
β^{HML}	−0.532	−0.414	0.261	0.147	0.445	0.405	0.192	0.386	0.576
β^{SMB}	1.22	1.01	0.676	0.849	0.582	0.808	0.782	0.584	0.556
	Fama-French 5 Factor Model: Equally Weighted								
α	10.467***	7.041***	0.699	2.353	0.567	−0.148	1.301	0.862	3.648*
	(2.63)	(2.18)	(1.92)	(2)	(1.94)	(1.81)	(3.1)	(1.89)	(1.89)
β^{MKT}	1.02	0.997	0.877	0.943	0.948	1.02	0.962	1.01	0.802
β^{HML}	−0.318	−0.243	0.286	0.2	0.431	0.417	0.331	0.401	0.665
β^{SMB}	0.955	0.8	0.706	0.82	0.63	0.85	0.792	0.579	0.553
β^{RMW}	−0.810	−0.622	0.070	−0.098	0.133	0.110	−0.028	−0.020	−0.043
β^{CMA}	−0.034	−0.041	−0.100	−0.070	−0.043	−0.092	−0.308	−0.022	−0.184
	Fama-French 3 Factor Model: Value Weighted								
α	3.331**	2.160*	0.420	−0.725	1.368	−2.727*	4.758**	−2.383*	−1.643
	(1.38)	(1.27)	(1.34)	(0.995)	(1.29)	(1.54)	(2.22)	(1.22)	(1.35)
β^{MKT}	1.01	1.17	0.991	1.01	0.751	0.996	0.8	1.06	1.16
β^{HML}	−0.397	−0.582	−0.0475	0.16	0.327	0.381	−0.112	0.352	0.558
β^{SMB}	0.019	0.127	−0.189	0.143	−0.079	0.212	−0.197	−0.089	−0.073
	Fama-French 5 Factor Model: Value Weighted								
α	3.813***	4.024***	−0.544	−2.114**	−1.291	−5.850***	2.232	−3.481**	−1.200
	(1.34)	(1.29)	(1.52)	(1.05)	(1.31)	(1.54)	(2.34)	(1.38)	(1.31)
β^{MKT}	0.993	1.09	1.03	1.06	0.859	1.12	0.883	1.1	1.13
β^{HML}	−0.394	−0.429	−0.102	0.0806	0.142	0.168	−0.138	0.284	0.638
β^{SMB}	−0.019	0.069	−0.144	0.208	0.024	0.337	−0.005	−0.041	−0.060
β^{RMW}	−0.103	−0.215	0.143	0.206	0.349	0.417	0.526	0.155	0.005
β^{CMA}	0.052	−0.233	0.045	0.066	0.233	0.256	−0.242	0.070	−0.189

Table 5 presents excess returns (α) over a three and a five factor Fama-French model of industry portfolios double sorted in terciles of their elasticity cash flow elasticity η and of their entry elasticity ζ.
I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), and for five factors the additional profitability (robust minus weak) and investment factor (conservative minus aggressive) all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns.
Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 1992 to 2017.

Table 6

Hi —Lo Portfolios based on both ζ elasticity and η elasticity

Portfolio Sort	Hi –Lo η_h			Hi –Lo ζ_h		
Portfolio Group by ζ_h	High ζ_h	Mid ζ_h	Low ζ_h	Low η_h	Mid η_h	High η_h
	Average Returns					
	6.07*	0.295	0.238	5.45	3.84	−0.379
	(3.61)	(1.27)	(1.88)	(3.79)	(2.78)	(1.87)
	Fama French 3 Factor Model					
α	4.67*	1.31	1.78	5.18	5.08**	2.29
	(2.62)	(1.12)	(1.81)	(3.56)	(2.05)	(1.7)
β^{MKT}	0.326	−0.0342	−0.0998	0.192	0.0312	−0.234
	(0.053)	(0.0209)	(0.041)	(0.0679)	(0.0445)	(0.0372)
β^{HML}	−0.793	−0.26	−0.198	−0.725	−0.693	−0.129
	(0.0943)	(0.0356)	(0.0664)	(0.11)	(0.0777)	(0.0563)
β^{SMB}	0.543	0.04	−0.0441	0.438	0.309	−0.149
	(0.125)	(0.0477)	(0.0611)	(0.138)	(0.0782)	(0.0404)
	Fama French 5 Factor Model					
	9.45***	2.37**	2.46	8.85***	7.74***	1.85
	(2.46)	(1.16)	(1.9)	(3.02)	(2.07)	(1.72)
β^{MKT}	0.147	−0.0735	−0.131	0.0626	−0.0703	−0.215
	(0.0446)	(0.0227)	(0.0485)	(0.0644)	(0.0461)	(0.0389)
β^{HML}	−0.598	−0.219	−0.118	−0.644	−0.572	−0.164
	(0.0726)	(0.0433)	(0.0804)	(0.0928)	(0.0909)	(0.0727)
β^{SMB}	0.239	−0.0299	−0.0472	0.152	0.149	−0.133
	(0.0597)	(0.0308)	(0.0587)	(0.0822)	(0.0531)	(0.0481)
β^{RMW}	−0.859	−0.195	−0.0444	−0.761	−0.462	0.0546
	(0.117)	(0.0517)	(0.0865)	(0.163)	(0.0933)	(0.0679)
β^{CMA}	0.072	0.0264	−0.161	0.282	0.00107	0.049
	(0.133)	(0.0645)	(0.104)	(0.167)	(0.115)	(0.106)

Table 6 presents excess returns (α) over a three and a five factor Fama-French model of long short industry portfolios double sorted in terciles of their elasticity cash flow elasticity η and of their entry elasticity ζ.
In column (1) to (3), I present portfolios that are long high cash flow elasticity η and short small η, for different terciles of their industry entry elasticity ζ. In column (4) to (6), I present portfolios that are long high industry entry elasticity ζ and short small ζ, for different terciles of their cash flow elasticity η.
I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), and for five factors the additional profitability (robust minus weak) and investment factor (conservative minus aggressive) all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns.
Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 1992 to 2017.

Table 7
List of Calibrated Parameters

Parameter	Symbol	Value
Household Preferences		
Subjective Discount Factor	β	0.998
Elasticity of Intertemporal Substitution (EIS)	ν	0.5
Relative risk aversion	γ	3
Aggregate Dynamics		
Death rate	δ	0.0025
Standard Deviation of Entry Shock ε^X	σ_X	0.02
Persistence of Entry Shock	ρ_X	0.8
Standard Deviation of Aggregate Productivity ε^A	σ_X	0.0025
Persistence of Aggregate Shock	ρ_A	0.8

Table 7 presents the set of calibrated parameters for the model. Household preferences are calibrated based on the asset pricing literature. The aggregate dynamics parameters are calibrated to match the aggregate dynamics of the economy: the average level of entry rates and the volatility of consumption.

Table 8
List of Non Targeted Moments in the Model

	Non Targeted Moments	
	Model	Data
Average Standard Deviation of Entry (annualized)		
High-ζ/Low-η (riskiest industry)	1.93	1.17
Low-ζ/Low-η	0.46	1.09
High-ζ/High-η	2.79	1.41
Low-ζ/High-η (least risky industry)	0.46	1.35
Aggregate Moments		
Std. Deviation of Consumption Growth (quarterly)	0.74	0.6
Average Risk-free rate	0.20	0.204
Standard Deviation of the Risk-free rate	0.30	0.177

Table 8 presents the list of non targeted moments in the model: the volatility of entry at the industry level and aggregate moments that I measure directly in the data.

Table 9
List of Targeted Moments and Estimated Parameters

	Panel A: Targeted Moments			
Sector	High-ζ_h / Low-η_h	Low-ζ_h / Low-η_h	High-ζ_h / High-η_h	Low-ζ_h / High-η_h
Elasticity of entry to X_t: ζ_h				
Model	0.425	0.100	0.612	0.100
Data	0.424	0.013	0.611	−0.084
Elasticity of profits to industry entry: η_h				
Model	−0.047	−0.076	0.002	0.000
Data	−0.047	−0.076	−0.004	0.007
Average Markup: μ_h				
Model	0.653	0.392	0.580	1.230
Data	0.520	0.579	0.615	0.555
Average Excess Returns (annualized)				
Model	9.467	6.987	7.275	5.187
Data	9.615	7.932	7.877	4.931
Entry rates (annualized)				
Model	0.575	0.199	0.422	0.226
Data	0.124	0.280	0.426	0.447
Exit rates (annualized)				
Model	0.575	0.199	0.422	0.226
Data	0.255	0.395	0.271	0.304

	Panel B: Parameter Estimates			
Sector	High-ζ_h / Low-η_h	Low-ζ_h / Low-η_h	High-ζ_h / High-η_h	Low-ζ_h / High-η_h
Entrepreneurs Supply Elasticity ζ				
Estimates	0.425	0.100	0.611	0.100
Standard errors	(0.014)	(0.019)	(0.025)	(0.057)
Entrepreneurs Costs Level f_e				
Estimates	4.981	26.158	3.544	26.793
Standard errors	(1.890)	(3.060)	(2.056)	(2.732)
Elasticity of Demand Parameter σ				
Estimates	4.584	6.265	4.649	2.368
Standard errors	(0.337)	(0.451)	(0.578)	(1.232)
Natural Size of Product Market $\overline{M}$				
Estimates	0.927	0.669	0.837	0.709
Standard errors	(0.122)	(43.387)	(0.710)	(0.643)
Exogenous death rate δ				
Estimates	0.575	0.199	0.422	0.226
Standard errors	(0.648)	(0.711)	(0.657)	(0.635)

In Panel A of Table 9, I present the list of targeted moments and their empirical counterpart: entry elasticity ζ, profit elasticity η, average markups, and average excess returns for each of the four industry portfolios.
In Panel B, I present the set of estimated parameters for each industry: the supply elasticity of entrepreneurs, ζ_h, the fixed costs of entry $f_{e,h}$, the level of consumer demand elasticity, σ_h, and the size of the product market, $\overline{M}_h$.

Figures

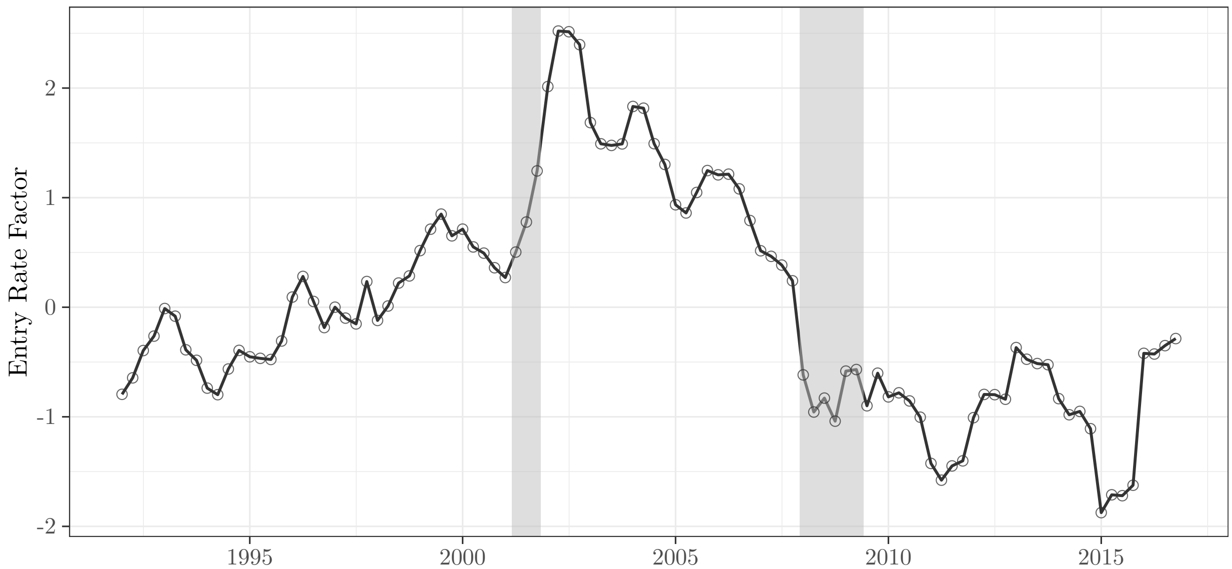

Figure 4. Entry Rates and Factors. Figure 4 presents the time series of the entry rate factor estimated in Section 2.1.

Online Appendix

Asset Pricing with Entry and Imperfect Competition

This Online Appendix includes the full derivation of the model (Appendix A) and details about the data construction (Appendix B), as well as a series of robustness tables and figures (Appendix C).

A Theory Appendix

A.1 Model Equilibrium derivation

In this section, I derive formally the model competitive equilibrium with H industries. First, I solve the static allocation before setting up the aggregate optimization program for the three parties in the economy: households, consumption good producers, and entrepreneurs.

Static Allocations. I take as given the dynamic state variables of the economy $(A_t, X_t, \{M_{h,t}\}_h)$. I solve for the static allocation at the industry level before aggregation. Recall that in industry h, households have transversal preferences of the following form:

$$f_h(c_h) = \frac{c_h^{\tau_h}}{\tau_h} - c_h \overline{M}_h^{1-\tau_h} \mathbf{C_h}^{\tau_h - 1},$$

where τ_h is defined from $\sigma_h = 1/(1-\tau_h)$ (or $\tau_h = (\sigma_h - 1)/\sigma_h$) represents the elasticity of substitution across varities. Given the Lagrangian multiplier on the consumer local industry budget constraint, λ_h, we write the inverse demand function from utility maximization as:

$$\lambda_h \cdot p_h(c_h) = c_h^{\tau_h - 1} \left(1 - \left(\frac{\mathbf{C_h}}{\overline{M}_h c_h} \right)^{\tau_h - 1} \right),$$

As in Zhelobodko et al. (2012) we define relative love for variety, r_h from the elasticity of the inverse demand as:

$$r_h(x) = \frac{1}{\mathcal{E}_h(x)} = -\left(\frac{c_h}{p_h(c_h)} \cdot \frac{\partial p_h(c_h)}{\partial c_h} \right)^{-1}$$

Note that we define the relative love for variety equation from $r_h(x) = -x \partial_{11} f_h(x, \mathbf{X}) / \partial_1 f_h(x, \mathbf{X})$. Under the symmetric equilibrium where all firms are homogeneous and produce the same quantity the relative love for variety simplifies to:

$$r_h(M_h) = \frac{1 - \tau_h}{1 - \overline{M}_h^{1-\tau_h} M_h^{\tau_h - 1}} = \frac{1}{\sigma_h} \cdot \frac{1}{1 - \overline{M}_h^{1/\sigma_h} M_h^{-1/\sigma_h}}$$

And the elasticity is:

$$\mathcal{E}_h(x) = \sigma_h \cdot \left(1 - \left(\frac{M_h}{\overline{M}_h} \right)^{-1/\sigma_h} \right)$$

In a monopolistic competition setting, firms take consumers' demand curves as given and maximize profits:

$$\max_{c_h} \pi(c_h) = \left(p(c_h) - \frac{w}{A} \right) \cdot c_h$$

The firm profit maximization leads to prices that are set at a markup over marginal cost:

$$p_h = \frac{\mathcal{E}_h(M_h)}{\mathcal{E}_h(M_h) - 1} \cdot \frac{w}{A}. \tag{A.1}$$

The net markups for industry h is:

$$\mu_h(M_h) = \frac{p_h}{w/A} = \frac{\mathcal{E}_h(M_h)}{\mathcal{E}_h(M_h) - 1}$$

Using the budget constraint, total expenditure in industry E_h equals total spending on goods $\int_0^{M_h} c_h(\omega)p_h(\omega)\mathrm{d}\omega$. I obtain the following symmetric industry equilibrium conditions:

$$c_h = \frac{E_h}{M_h p_h} = \left(1 - \frac{1}{\mathcal{E}_h(M_h)}\right) \cdot \frac{A}{w} \cdot \frac{E_h}{M_h}$$
$$\pi_h = \frac{1}{\mathcal{E}_h(M_h)} \frac{E_h}{M_h}$$

Finally the local industry level consumption index is:

$$\mathcal{C}_h = \int_0^{M_h} f_h(c_h, \mathbf{C}_h)\mathrm{d}\omega = \left(\frac{AE_h}{wM_h} \cdot \left(1 - \frac{1}{\mathcal{E}_h(M_h)}\right)\right)^{\frac{\sigma_h - 1}{\sigma_h}} \cdot \frac{\sigma_h}{\sigma_h - 1} M_h \cdot \left(1 - \frac{\sigma_h - 1}{\sigma_h}\left(\frac{M_h}{\overline{M}_h}\right)^{-\frac{1}{\sigma_h}}\right) l$$

From the local allocations I derive aggregate allocations. The upper-tier program is:

$$\max\ \mathcal{C} = \prod_h [s_h \mathcal{C}_h]^{\frac{\alpha_h}{s_h}} \tag{A.2}$$

given the budget constraint $\sum_h E_h \leq E$, where E_h is the industry level expenditure and E the aggregate consumption expenditure level. The first order condition reads

$$\partial_{E_g}\mathcal{C} = \partial_{E_h}\mathcal{C} = \frac{\alpha_h}{s_h} \cdot \frac{\mathcal{C}}{\mathcal{C}_h} \cdot \frac{\partial \mathcal{C}_h}{\partial E_h} = \alpha_h \cdot \frac{\mathcal{C}}{E_h},$$

where the last equality is due to the fact that $\partial\mathcal{C}_h/\partial E_h = \tau_h \mathcal{C}_h/E_h$ and we assume the normalization $s_h = \tau_h$. Using the budget constraint I obtain that consumers have constant expenditure shares across all industries. This is due to the constant elasticity of industry level utility to the level of expenditure:

$$E_h = \alpha_h E.$$

I conclude by deriving the allocations as a function of aggregate state variables (endogenous or exogenous). From the fixed expenditure shares I obtain local consumption and the main object of interest, firm profit within an industry:

$$c_h = \left(1 - \frac{1}{\mathcal{E}_h(M_h)}\right) \cdot \frac{A}{w} \cdot \frac{\alpha_h}{M_h} \cdot \mathcal{C}, \tag{A.3}$$
$$\pi_h = \frac{1}{\mathcal{E}_h(M_h)} \cdot \frac{\alpha_h}{M_h} \cdot \mathcal{C}, \tag{A.4}$$

where I used the normalization that aggregate consumption $\mathcal{C}$ is the numeraire.

Households Dynamic Problem. The representative household has recursive preferences of the Epstein-Zin type. He maximizes his continuation utility J_t over sequences of the consumption index C_t:

$$J_t = \left[(1-\beta)C_t^{1-\nu} + \beta\left(\mathsf{R}_t(J_{t+1})\right)^{1-\nu}\right]^{\frac{1}{1-\nu}},$$

where β is the time preference parameter, ν is the inverse of the inter-temporal elasticity of substitution (IES) and γ is the coefficient of relative risk aversion (CRRA). $\mathsf{R}_t(J_{t+1}) = [\mathbf{E}_t\{J_{t+1}^{1-\gamma}\}]^{1/(1-\gamma)}$ is the risk adjusted continuation utility. The representative household is subject to his sequential budget constraint:

$$\begin{aligned}\sum_h \Big[\mathcal{C}_t\ + x_{h,t+1} v_{h,t}\frac{M_{h,t+1}}{1-\delta} + x^e_{h,t+1} v^e_{h,t}\Big] \\ \leq w_t L + \sum_h \left[x_{h,t} M_{h,t}(v_{h,t} + \pi_{h,t}) + x^e_{h,t}(v^e_{h,t} + \pi^e_{h,t})\right].\end{aligned} \tag{A.5}$$

$x_{h,t}$ are the shares held by the representative household in a mutual fund specialized in consumption good producers of industry h; $x^e_{h,t}$ are shares held in a mutual fund that owns all the innovators in industry h. Households invest today by buying shares $x_{h,t+1}, x^e_{h,t+1}$ of the mutual funds at their respective market price: $v_{h,t}M_{h,t+1}/(1-\delta)$ and $v^e_{h,t}$. They receive proceeds from their shares in the funds as income, $M_{h,t}(v_{h,t}+\pi_{h,t})$ for consumption goods and $v^e_{h,t} + \pi^e_{h,t}$ from the innovation sector.

I call the respective Lagrange multipliers for equations A.5 κ_t. Optimization conditions on respectively $\mathcal{C}_{t+1}, \mathcal{C}_t, x_{h,t+1}$ and $x^e_{h,t+1}$ read:

$$\begin{aligned}
&\kappa_{t+1} = \partial J_t / \partial C_{t+1}, \\
&\kappa_t = \partial J_t / \partial C_t, \\
&\kappa_t v_{h,t} = (1-\delta)\mathbf{E}_t \left\{ \kappa_{t+1}(v_{h,t+1} + \pi_{h,t+1}) \right\}, \\
&\kappa_t v^e_{h,t} = \mathbf{E}_t \left\{ \kappa_{t+1}(v^e_{h,t+1} + \pi^e_{h,t+1}) \right\}.
\end{aligned} \tag{A.6}$$

In this environment it is possible to price any asset in zero net supply by adding them to the sequential budget constraint; their valuation would be given by the standard Euler equation as is the case for the innovators and the consumption good producers. Note that since households supply labor inelastically, the price of labor adjust such that the budget constraint holds exactly.

Entrepreneurs. Entrepreneurs operate a technology that is in limited supply. They hire labor to create firms that will produce new varieties of goods in their industry. They sell the new firms at their market value $v_{h,t}$, hence their profit function reads:

$$\max_{M^e_{h,t}} \pi^e_{h,t} = M^e_{h,t} v_{h,t} - w_t L^e_{h,t},$$

subject to their production frontier, that I specify using a convex cost function:

$$\Phi_h(M^e_{h,t}, M_{h,t}) = \frac{\exp(f_{e,h})}{1+\zeta_h^{-1}} \left(\frac{M^e_{h,t}}{M_{h,t}} \right)^{1+\zeta_h^{-1}} M_{h,t} \leq X_t L^e_{h,t}.$$

Innovators are in perfect competition with each other. Hence there is no option value of firms entry, and maximizing innovators value is equivalent to maximizing their static profit. I call the Lagrange multiplier on the cost $q_{h,t}$, the optimization with respect to $M^e_{i,t}, L^e_{i,t}$ program reads:

$$v_{h,t} = q_{h,t} \exp(f_{e,h}) (M^e_{h,t}/M_{h,t})^{\zeta_h^{-1}}, \tag{A.7}$$

$$q_{h,t} = w_t / X_t. \tag{A.8}$$

Dynamic Equilibrium. An equilibrium is a set of prices $(p_{h,t}, w_t, v_{h,t}, v^e_{h,t})$, a set of allocations $(c_{h,t}, \mathcal{C}_{h,t}, \mathcal{C}_t, L^e_{h,t}, L^p_{h,t}, M^e_{h,t}, M_{h,t}, x_{h,t}, x^e_{h,t})$ such that: (a) given prices, allocations maximize the households program; (b) given prices allocations maximize firms profits; (c) labor markets, good markets and asset markets clear.

To characterize the equilibrium, I derive the aggregate production function, firms' valuation and their dynamic through the Euler equation. But first I calculate the equilibrium profit of the differentiated varieties producers in each industry.

Within each industry the firm equilibrium is symmetric. Firms face the same optimization program, and the same consumer demand curve; hence they price is constant across varieties in one industry $p_{h,t}(\omega) = p_{h,t}$ and so is demand. The price of an individual variety in the industry is given by equation (A.1). Local demands and profits are given in equations (A.3) and (A.4) respectively. Finding the wage requires some more work. First notice that:

$$\begin{aligned}
\mathcal{C}_h &= \frac{c_h^{\tau_h}}{\tau_h} M_h \left[1 - \tau_h \cdot (M_h / \overline{M}_h)^{\tau_h - 1} \right] \\
c_h &= \frac{A}{w} \cdot (1 - 1/\mathcal{E}_h(M_h)) \cdot \frac{\alpha_h}{M_h} \cdot \mathcal{C}
\end{aligned}$$

Using the definition of $\mathcal{C}$ from (A.2), I find:

$$\begin{aligned} w_t &= A_t \prod_h \left[\alpha_h M_{h,t}^{\frac{1}{\sigma_h - 1}} \cdot (1 - 1/\mathcal{E}_h(M_{h,t})) \cdot \left(1 - \tau_h (M_{h,t}/\overline{M}_h)^{\tau_h - 1}\right)^{\frac{1}{\tau_h}} \right]^{\alpha_h} \\ &= A_t \prod_h [W_h(M_{h,t})]^{\alpha_h} = A_t \mathbf{W}(\{M_{h,t}\}_h) \end{aligned} \tag{A.9}$$

Firm value is set by the marginal decision of the innovation sector (A.7, A.8), their optimization conditions give us:

$$v_{h,t} = \frac{w_t}{X_t} \exp(f_{e,h}) \left(M_{h,t}^e / M_{h,t}\right)^{\zeta_h^{-1}}.$$

Finally the one period ahead stochastic discount factor $S_{t,t+1}$ is given in equilibrium by:

$$S_{t,t+1} = \frac{S_{t+1}}{S_t} = \beta \left(\frac{C_{t+1}}{C_t}\right)^{-\nu} \left(\frac{J_{t+1}}{\mathsf{R}_t(J_{t+1})}\right)^{\nu - \gamma}$$

At last using (A.6), I derive the Euler equation for a firm in industry h:

$$v_{h,t} = (1 - \delta) \mathbf{E}_t \frac{S_{t+1}}{S_t} \left\{ v_{h,t+1} + \alpha_h r_h(M_{h,t+1}) \frac{\mathcal{C}_{t+1}}{M_{h,t+1}} \right\} \tag{A.10}$$

I calculate the aggregate consumption index as a function of employment used for consumption production. Labor used in each industry for production is $L_{h,t}^p = \int \mathrm{d}\omega l_{h,t}(\omega)$. Using the property of the symmetric equilibrium I can rewrite this as $A_t L_{h,t}^p = M_{h,t} c_{h,t} / A_t$. Adding up the labor used in each industry such that $L_t^p = \sum_h L_{h,t}^p$, aggregate consumption reads:

$$\mathcal{C}_t = \frac{\prod_h [W_h(M_{h,t})]^{\alpha_h}}{\sum_h \alpha_h (1 - 1/\mathcal{E}_h(M_{h,t}))} \cdot A_t L_t^p \tag{A.11}$$

There is a distortion factor that depends on the product market structure in each industry. Production is below that of an economy with standard industry preferences with perfect competition.

Finally, in this paper I do not focus on the valuation of innovation specific firms, $v_{h,t}^e$.[25] However the optimization condition from the households yield an Euler equation specific to the innovation sector:

$$\begin{aligned} v_{h,t}^e =& \mathbf{E}_t \frac{S_{t+1}}{S_t} \left\{ v_{h,t}^e + \pi_{h,t}^e \right\} = \\ & \mathbf{E}_t \frac{S_{t+1}}{S_t} \left\{ v_{h,t}^e + \frac{w_t}{X_t} \left[M_{h,t+1}^e \partial_1 \Phi_h(M_{h,t+1}^e, M_{h,t+1}) - \Phi_h(M_{h,t+1}^e, M_{h,t+1}) \right] \right\} \end{aligned}$$

A.2 Other Results

A.2.1 Asset Pricing Elasticities

Response of the SDF to Entry Shocks — In Section 3.3.3 I use the fact that contemporaneous consumption responds negatively to entry shocks while continuation utility responds positively:

$$\partial_{\varepsilon_t^X} C_t \leq 0, \tag{A.12}$$

$$\partial_{\varepsilon_t^X} J_t \geq 0. \tag{A.13}$$

To show (A.12), I use the investment the definition of aggregate consumption in (A.11). The only variable that are not predetermined at time $t - 1$ are A_t and L_t^p. Hence the shock affects aggregate consumption

[25] See Papanikolaou (2011) for an analysis separating returns in the innovation (investment goods) sector and in the consumption good sector.

through its effects on labor. The labor resource constraint links production labor to the labor used for firm entry, $L_t^p = L - \sum_h L_{h,t}^e$. Thus the effect of the entry shock on C_t depends on how does $L_{h,t}^e$ respond to the entry shock. From the entrepreneur production function, the quantity of labor depends on the mass of incumbents firms $M_{h,t}$ and the mass of new entrants $M_{h,t}^e$. Since $M_{h,t}$ is predetermined at $t+1$, the response only depends on $M_{h,t}^e$ which is determined by the entrepreneur first order condition:

$$M_{h,t}^e \propto \left(w_t^{-1} X_t v_{h,t}\right)^{\zeta_h}$$

Equation (A.9) ensures that wages are predermined at time $t-1$ up to aggregate productivity A_t. The first order, partial equilibrium, effect of X_t on $M_{h,t}$ has an elasticity of ζ_h. An increase in entry of one percent leads to an increase of the level of entry of ζ_h percents. The partial equilibrium takes the industry valuations $v_{h,t}$ as given and does not capture the total elasticity. The overall elasticity is smaller as $v_{h,t}$ falls in response to the mass of new firms entry increasing: $\partial \log M_{h,t}^e = \zeta_h + \zeta_h \partial \log v_{h,t}$. The last term represents equilibrium price effect and is always smaller than the direct partial equilibrium effect. Let's imagine it is larger: then the mass of new firms decreases in response to the entry shock, leading to higher cash-flows in the future and relatively higher valuations, such that $\partial \log v_{h,t} > 0$, a contradiction.

As X_t increases, the investment opportunity set of the aggregate economy expands. It is therefore to produce the same amount of new firms using fewer resources, that are freed for the production of consumption good. Hence the overall effect on the continuation utility of the representative agent cannot be negative leading to (A.13).

Expected Returns — In the model asset pricing Section, I claim expected returns can be expressed as follow (see equation 3.13):

$$\mathbf{E}_t\left\{R_{h,t}^e\right\} \simeq \mathrm{rp}_t^A \operatorname{Cov}_t\left(\frac{v_{h,t+1}+\pi_{h,t+1}}{v_{h,t}}, \varepsilon_{t+1}^A\right) + \mathrm{rp}_t^X \operatorname{Cov}_t\left(\frac{v_{h,t+1}+\pi_{h,t+1}}{v_{h,t}}, \varepsilon_{t+1}^X\right).$$

Starting with the pricing Euler equation, I have:

$$\mathbf{E}_t\left\{R_{h,t}^e\right\} = -\frac{\operatorname{Cov}_t(R_{h,t}^e, S_{t+1})}{\mathbf{E}_t(S_{t+1})}$$

Our model is a two-factor model in its two exogenous state variables, hence I have:

$$R_{h,t+1} = \frac{v_{h,t+1}+\pi_{h,t+1}}{v_{h,t}} = f(\varepsilon_{t+1}^X, \varepsilon_{t+1}^A; (X_t, A_t))$$

Using a linear approximation of the function f, I find $R_{h,t+1} = f_X \varepsilon_{t+1}^X + f_A \varepsilon_{t+1}^A$. Within the linear approximation the exposure to shocks of stock returns are given by $f_K = \operatorname{Cov}_t\left(R_{h,t+1}, \varepsilon_{t+1}^K\right)$. Given the definition of rp^A and rp^X, plugging back into the expression for expected returns concludes the derivation.

A.2.2 Industry Linkages

Consumers have Cobb-Douglas preferences over industry consumption aggregates:

$$C = \Pi_h \left[s_h \mathcal{C}_h\right]^{\frac{\alpha_h}{s_h}}$$

This leads to fixed industry expenditure shares from the aggregate: $E_h = \alpha_h C$. Hence if industry h_1 becomes relatively more productive, i.e. cheaper, it will affect aggregate utility but it will not affect the equilibrium within industry h_2 and hence its elasticities η_2 and ζ_2. Note that this a direct consequence of the Cobb-Douglas assumption.

It is possible to relax this assumption and consider spillovers across industries by introducing a demand with constant elasticity of substitution (CES) across industries as follows:

$$C = \left[\sum_h s_h^{\frac{1}{\theta}} C_h^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}$$

The demand for industry consumption bundle does not respect the fixed expenditure shares from the Cobb-Douglas case and we have the following:

$$P_h C_h = \eta_h \left(\frac{P_h}{P} \right)^{1-\theta} PC$$

where P is the aggregate price index, PC is total aggregate expenditure, $P_h C_h$ is the expenditure in sector h. The aggregate is price index as $P^{1-\theta} = \sum_h P_h^{1-\theta}$. Thus any industry linkages from industry $h = 1$ to industry $h = 2$ goes through the effect of industry 1 on the aggregate price index P:

$$\frac{\partial \log P_2 C_2}{\partial \log P_1} = (\theta - 1) \cdot \frac{P_1 C_1}{PC} \tag{A.14}$$

If industry 1 becomes relatively more productive (P_1 falls), consumer demand shifts from industry h_2 to industry h_1. The size of the effect depends on both the elasticity of substitution across industries (θ) and the expenditure share of the "shocking" industry, $P_1 C_1/(PC)$ in our example.[26] While there are no estimates in the literature of the demand elasticity across industries, there exist estimates of the elasticity within, as in Broda and Weinstein (2006).[27] Assuming that the across industry is lower than the within industry elasticity, I take for θ the average value of low elasticity industries which is 1.4. To form an estimate of the expenditure shares by sectors I use the BEA tables of value added as a fraction of GDP. The expenditure shares are available from the BEA at a two-digits industries sectoral level. The highest expenditure share among industries is shared by manufacturing, 11.7% and real estate 13.3%. Thus a generous upper bound on the industry linkages in a standard model would be of 0.05. An decrease in the price index of 1% in industry 1 would lead to a decrease in the expenditure share of industry 2 of 0.05%. The magnitude is therefore small enough to consider the Cobb-Douglas approximation of fixed expenditure shares appropriate.

[26] This is a well known result in trade theory that has proven to be general in a large class of general equilibrium models, see Arkolakis et al. (2012)

[27] I downloaded data at the 3 digits level (the most disaggregated) from David Weinstein's website: http://www.columbia.edu/~dew35/TradeElasticities/TradeElasticities.html

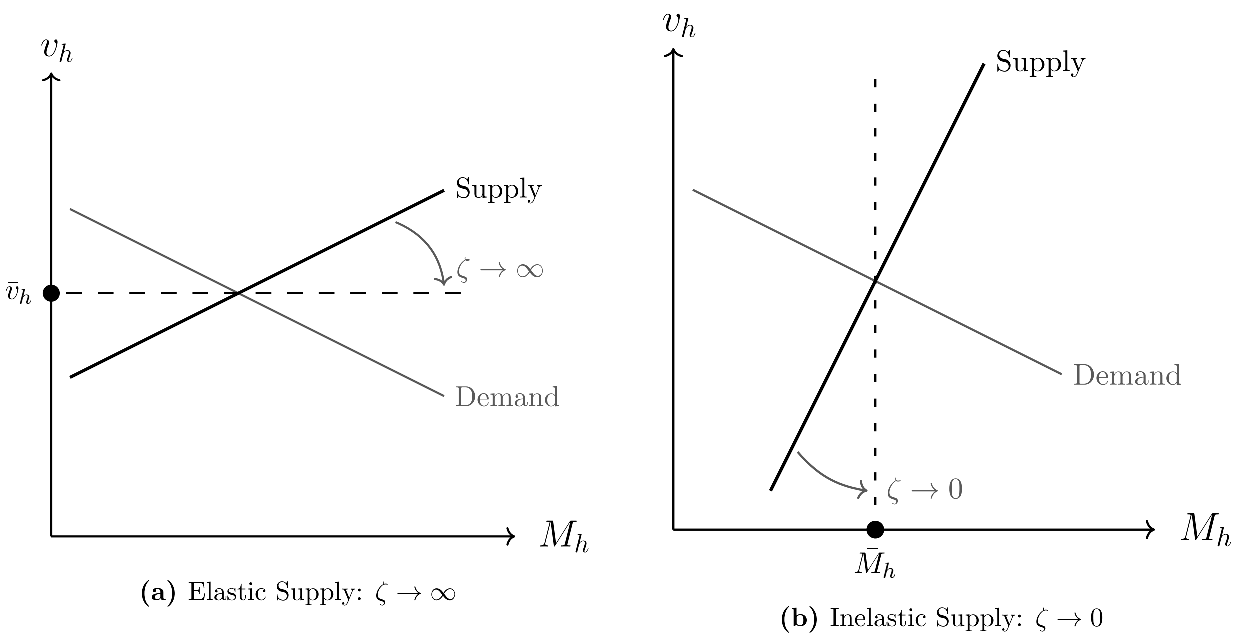

Figure A.1. Elasticity of the Supply Curve of New Firms

B Appendix —Measurement and Data Construction

B.1 Data construction

Industry Data on Entry Rates. I use the Quarterly Census of Employment and Wages (QCEW) to construct establishment level entry rates. I use the rate of entry in a 4-digit NAICS industry as the percent change of establishment from one quarter to the next:

$$\Delta M_{h,t} = \frac{M_{h,t} - M_{h,t-1}}{M_{h,t-1}},$$

where $M_{h,t}$ is the number of establishments in a product market h in a given quarter t. Such measure generate net entry rates of establishment entries minus exits. For robustness purposes I construct a measure of entry based on small establishments only (below 100 employees). This weighting scheme only plays a role while estimating the factor and factor loadings in the interactive fixed effects specification, as the time series within industries is not modified.

To capture the aggregate factor as described in Section 2, I estimate a factor model with industry fixed effects as:

$$\begin{aligned} \Delta M_{ht} &= \mathbf{Z}'_{ht}\beta + u_{ht} \\ u_{ht} &= a_h + \zeta_h \mathbf{F}_t + \varepsilon_{ht}, \end{aligned}$$

where ΔM_{ht} is the entry rate (based on establishments) in a given industry; $\mathbf{Z}_{ht}$ is a vector of industry controls which include the past number of establishments $M_{h,t-1}$ and aggregate productivity; I also allow for industry fixed effects in the form of a_h to control for unobserved heterogeneity at the industry level. I jointly estimate the model to find both a cross section of loadings $(\zeta_h^{(1)}, \zeta_h^{(2)}, \dots)$ for each industry i which corresponds to each factor $\mathbf{F}_t = (F_t^{(1)}, F_t^{(2)}, \dots)$.

Measuring Markups. I follow Loecker and Eeckhout (2017) to construct a measure of markups at the firm level that I aggregate at the four-digit industry level. I estimate firms' production function as:

$$Q_{it} = \Omega_{it} F_t(\mathbf{V}_{it}, K_{it}),$$

where $\mathbf{V}$ is a vector of variable inputs, K_{it} its capital stock and Ω_{it} a firm specific productivity. Considering the firm first order condition with respect to a given variable input V_{it}, we are able to express markups as the inverse expenditure ratio for input V_{it} multiplied by its output elasticity θ_{it}^V:

$$\mu_{it} = \theta_i^V \cdot \frac{P_{it} Q_{it}}{P_{it}^V V_{it}}$$

I observe both the numerator, $P_{it}Q_{it}$ which are compustat sales and the denominator, $P_{it}^V V_{it}$ is the total variable cost of production measured by compustat cost of goods sold. To recover the input elasticity θ_i^V, I estimate the firm production function above and this gives me an estimate of markups for each firm.

Selection of Firms and Industries. I include all firms with listed securities on the AMEX, NASDAQ, or NYSE that have a match in the CRSP monthly file and in the COMPUSTAT annual file from 1980 to 2012. I exclude regulated industries and financials from the sample.[28] To be included in my sample, firms must have a stock price, shares outstanding and a three-digit NAICS codes. Moreover, firms in CRSP/COMPUSTAT must have their three-digit NAICS code in the entry dataset from the BLS (eighty-five). I define industries at three-digit level of the NAICS classification. Moreover, the data on entry rates is aggregated at the three-digit NAICS code level, which allows for a match at the industry level of the Bureau of Labor Statistics (BLS) data with the CRSP/COMPUSTAT sample.

[28] My results are robust to including regulated and financials. However, their price-setting decision might be regulated, and linking concentration to markups in such industries is difficult. The excluded two-digits NAICS codes are 22, 52, and 92.

Firm level quantities. I define cash-flows following Rajan and Zingales (1998): Cash-flows are earnings before interest, taxes, depreciation and amortization from COMPUSTAT (item `EBITDA`) plus decreases in inventories (item `INVT`), decreases in receivables (item `RECT`) and increases in payables (item `AP`), all scaled by assets (item `AT`). Description of stock market data is in the body of the paper.

B.2 Estimating the Market Price of Risk

To test the model's prediction about risk factors, I estimate a linear approximation of the SDF (see Equation 3.13):

$$S = b_0 - b_A \varepsilon^A - b_X \varepsilon^X, \tag{B.1}$$

where ε^A and ε^X are the aggregate productivity and entry shocks respectively. In this approximation, the price of risk for each factor is constant. For aggregate productivity I use the return on the value-weighted market portfolio from CRSP. For the entry shock, I use two different measures: I construct a factor mimicking portfolios guided by the model and the results of the previous section. The long-short portfolio from Table 6, noted $(\Delta_\zeta R^e|\text{low-}\eta)$, that captures differential exposure to the entry shock through different elasticities of industry entry to aggregate entry, but only in industries where profits are exposed to entry. The factor mimicking portfolio is normalized to correlate positively with entry shocks. Similarly I construct a factor mimicking portfolio based on the η elasticity noted $(\Delta_\eta R^e|\text{high-}\zeta)$, that captures differential exposure of profits at the industry level for industries that are already exposed to the aggregate entry factor (the high ζ elasticity industries).

I estimate the model parameters of the SDF using the generalized method of moments (GMM). I use the moment restrictions on the excess rate of return of any asset that is imposed by no arbitrage through the Euler equation:

$$\mathbf{E}\{S R_i^e\} = 0. \tag{B.2}$$

In my estimation, I use portfolios returns in excess of the risk-free rate, R_i^e, so the mean of the SDF is not identified from the moment restrictions. I choose the common normalization $\mathbf{E}\{S\} = 1$, the moment conditions now read:

$$\mathbf{E}\{R_i\} - R_f = -\operatorname{Cov}(S, R_i^e); \tag{B.3}$$

this is equivalent to equation (3.13), with the set of conditional moments replaced by unconditional ones. I evaluate the model's ability to price assets based on the residual of the moment conditions. I compute the J-test of over-identifying restrictions of the model, that all the pricing errors are zero. I adjust standard errors of the GMM estimator using Newey-West with a maximum lag of 2 years. It is always a challenge to estimate the SDF using the whole cross section of stock returns, because covariances are measured with errors and firm level stock returns are volatile. To reduce measurement errors, asset pricers resort to an aggregation of firm level returns into a smaller number of portfolios; these test assets are usually aggregation of stocks along meaningful economic characteristics. Indeed for an accurate estimation of b_A or b_X, an asset pricer needs significant dispersion in exposures to the risk factor. Since industry returns are already an aggregation of stocks, I use the 9 double sorted portfolios introduced in Table 5 and the Fama-French 49 industry portfolios (see Fama and French (1997)) as test assets.

Results for either factor mimicking portfolios are in Tables C.9 and C.10.

C Appendix —Supplementary Tables and Figures

Table C.1

Top and bottom 5 industries by Elasticity, ζ and η

Industry Description	NAICS **code**	**Elasticity**
Panel A: Elasticity of industry entry to aggregate entry: ζ_h		
Rail transportation	4821	−30.7
Other hospitals	6223	−26.8
Offices of real estate agents and brokers	5312	−24.5
Postal service	4911	−24.3
Electronic markets and agents and brokers	4251	−24
Communications equipment manufacturing	3342	19.1
Hunting and trapping	1142	26.3
Magnetic media manufacturing and reproducing	3346	27.6
Software publishers	5112	31.3
Tobacco manufacturing	3122	64.6
Panel B: Elasticity of cash-flows to industry entry: η_h		
Local messengers and local delivery	4922	−2.01
Commercial machinery repair and maintenance	8113	−1.57
Urban transit systems	4851	−1.16
Other textile product mills	3149	−0.956
Taxi and limousine service	4853	−0.639
Support activities for road transportation	4884	1.07
Florists	4531	2.08
Other crop farming	1119	3.05
School and employee bus transportation	4854	3.27
Performing arts companies	7111	11.2

Table C.1 reports the five largest and smallest measured elasticities of industry entry to aggregate shocks (ζ) and cash flow to entry (η).
Note that the ζ elasticity is the not normalized and represent the factor loading from the interactive fixed effect regression.

C.1 Robustness Tables

Table C.2

Portfolios Sorted on the Elasticity of Industry Small Firms Entry to Aggregate Entry: ζ

Portfolio quintiles	High ζ_h	4	3	2	Low ζ_h	Hi–Lo	High ζ_h	4	3	2	Low ζ_h	Hi–Lo
	Average Returns: Equally Weighted						Average Returns: Value Weighted					
	14.16***	14.31***	11.40***	10.53**	9.21**	4.95***	10.49**	8.48***	7.60**	6.77**	5.85*	4.64*
	Fama-French 3 Factor Model: Equally Weighted						Fama-French 3 Factor Model: Value Weighted					
α	3.59*	5.00**	1.50	0.03	−0.80	4.39***	2.64*	2.93***	0.16	−1.03	−1.52*	4.16**
	(1.98)	(2.4)	(1.49)	(1.81)	(1.4)	(1.57)	(1.55)	(1.01)	(1.11)	(1.34)	(0.893)	(2.08)
β^{MKT}	1.2	1.08	1	1.02	1.06	0.139	1.2	0.871	0.936	0.94	1.01	0.185
β^{HML}	−0.230	−0.440	0.176	0.396	0.067	−0.297	−0.506	−0.261	0.059	0.238	0.015	−0.520
β^{SMB}	1.02	1.14	0.821	0.757	0.838	0.184	0.184	−0.0728	0.122	0.0265	−0.109	0.294
	Fama-French 5 Factor Model: Equally Weighted						Fama-French 5 Factor Model: Value Weighted					
α	6.81***	8.84***	2.39	0.19***	0.91*	5.90***	4.52***	2.55***	−1.75	−3.09***	−1.62*	6.14***
	(2.28)	(2.52)	(1.93)	(2.05)	(1.79)	(1.51)	(1.49)	(0.938)	(1.11)	(1.13)	(0.97)	(2.17)
β^{MKT}	1.087	0.949	0.964	1.005	0.995	0.092	1.130	0.894	1.000	1.009	1.019	0.111
β^{HML}	−0.078	−0.283	0.277	0.436	0.174	−0.252	−0.384	−0.338	−0.023	0.152	0.006	−0.390
β^{SMB}	0.852	0.922	0.811	0.769	0.765	0.088	0.106	−0.090	0.227	0.143	−0.107	0.213
β^{RMW}	−0.539	−0.677	−0.062	0.020	−0.247	−0.292	−0.266	−0.024	0.330	0.363	0.010	−0.275
β^{CMA}	−0.052	0.013	−0.201	−0.106	−0.112	0.060	−0.135	0.193	0.007	−0.005	0.016	−0.150

Table C.2 presents excess returns (α) over a three and a five factor Fama-French model of industry portfolios sorted by quintiles of their elasticity ζ of industry entry to aggregate entry shocks. I measure the industry entry elasticity, ζ, based on small firms only (under 100 employees).
I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), and for five factors the additional profitability (robust minus weak) and investment factor (conservative minus aggressive) all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns. Portfolios returns are either equally weighted (columns (1) to (6)) or value weighted (columns (7) to (12)). Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 1992 to 2017.

Table C.3

Portfolios based on both ζ elasticity measured using Industry Small Firms Entry and η elasticity

Portfolio - ζ_h	High ζ_h			Mid ζ_h			Low ζ_h		
Portfolio - η_h	Low	Mid	High	Low	Mid	High	Low	Mid	High
	Fama-French 3 Factor Model: Equally Weighted								
α	5.636**	2.900	−1.008	1.974	0.495	−0.403	−1.035	−0.148	0.001
	(2.47)	(2.15)	(1.9)	(1.61)	(2.28)	(1.58)	(2.15)	(1.67)	(1.8)
β^{MKT}	1.15	1.14	1.06	0.93	1.09	1.03	1.11	1.13	1.01
β^{HML}	−0.467	−0.268	0.547	0.198	0.161	0.461	0.273	0.0853	0.169
β^{SMB}	1.16	1.02	0.823	0.777	0.881	0.732	0.907	0.733	0.848
	Fama-French 5 Factor Model: Equally Weighted								
α	9.746***	5.889**	−2.079	2.643	2.465	−1.066	−0.023	1.333	1.562
	(2.6)	(2.31)	(2.11)	(1.96)	(2.55)	(1.79)	(2.61)	(2.13)	(2.12)
β^{MKT}	0.995	1.02	1.1	0.898	1	1.05	1.07	1.07	0.949
β^{HML}	−0.27	−0.157	0.495	0.289	0.338	0.476	0.324	0.181	0.292
β^{SMB}	0.931	0.834	0.882	0.782	0.829	0.802	0.853	0.668	0.795
β^{RMW}	−0.695	−0.556	0.179	−0.023	−0.207	0.184	−0.167	−0.213	−0.191
β^{CMA}	−0.052	0.070	0.017	−0.201	−0.294	−0.145	−0.021	−0.098	−0.176
	Fama-French 3 Factor Model: Value Weighted								
α	3.938***	2.807**	−2.265	1.863	0.065	−0.656	−3.787**	−1.249	0.195
	(1.38)	(1.37)	(2.01)	(1.22)	(2.11)	(1.31)	(1.63)	(1.38)	(1.48)
β^{MKT}	0.994	1.09	1.1	0.854	0.88	0.972	1.17	1.03	0.952
β^{HML}	−0.405	−0.372	0.513	0.0864	0.192	0.267	0.249	−0.078	−0.0846
β^{SMB}	0.015	0.132	0.360	−0.027	0.065	0.126	0.187	−0.018	−0.226
	Fama-French 5 Factor Model: Value Weighted								
α	4.278***	3.843***	−5.986***	−1.134	−0.814	−3.285***	−3.671**	−1.290	−1.126
	(1.36)	(1.27)	(1.69)	(1.01)	(2)	(1.13)	(1.71)	(1.4)	(1.69)
β^{MKT}	0.983	1.05	1.25	0.971	0.912	1.08	1.17	1.03	1.01
β^{HML}	−0.403	−0.293	0.288	−0.0543	0.168	0.12	0.276	−0.0542	−0.213
β^{SMB}	−0.014	0.095	0.534	0.141	0.127	0.257	0.195	0.002	−0.199
β^{RMW}	−0.079	−0.130	0.559	0.511	0.177	0.413	0.013	0.046	0.123
β^{CMA}	0.042	−0.109	0.197	0.028	−0.049	0.100	−0.072	−0.083	0.229

Table 5 presents excess returns (α) over a three and a five factor Fama-French model of industry portfolios double sorted in terciles of their elasticity cash flow elasticity η and of their entry elasticity ζ. I measure the industry entry elasticity, ζ, based on small firms only (under 100 employees).
I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), and for five factors the additional profitability (robust minus weak) and investment factor (conservative minus aggressive) all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns.
Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 1992 to 2017.

Table C.4

Portfolios Sorted on the Elasticity of Industry to Aggregate Entry: ζ_h — Unlevered Returns

Portfolio quintiles	High ζ_h	4	3	2	Low ζ_h	Hi–Lo	High ζ_h	4	3	2	Low ζ_h	Hi–Lo
	Average Returns: Equally Weighted						Average Returns: Value Weighted					
	12.73^{**}	10.43^{**}	8.38^{**}	7.72^{**}	6.09^{**}	6.64^{*}	8.73^{**}	7.80^{**}	6.08^{***}	5.69^{**}	5.14^{**}	3.59
	Fama-French 3 Factor Model: Equally Weighted						Fama-French 3 Factor Model: Value Weighted					
α	4.26^{*}	2.04	0.84	0.41	−1.54	5.80^{**}	3.38^{***}	0.76	0.38	−1.22	−0.80	4.17^{**}
	(2.4)	(1.29)	(1.21)	(1.08)	(0.984)	(2.52)	(1.09)	(1.26)	(1.01)	(1.02)	(0.995)	(1.79)
β^{MKT}	1.04	0.974	0.782	0.719	0.788	0.249	0.928	1.08	0.707	0.802	0.795	0.134
β^{HML}	−0.602	−0.236	0.068	0.225	0.146	−0.747	−0.489	−0.426	0.134	0.243	0.029	−0.519
β^{SMB}	1.11	0.802	0.658	0.554	0.573	0.539	−0.0444	0.0977	0.00933	0.0819	−0.0347	−0.00971
	Fama-French 5 Factor Model: Equally Weighted						Fama-French 5 Factor Model: Value Weighted					
α	8.83^{***}	4.71^{**}	1.16	0.05^{***}	-1.29^{**}	10.12^{***}	3.72^{***}	3.31^{**}	−1.22	-2.83^{***}	-2.12^{**}	5.85^{***}
	(2.33)	(1.6)	(1.41)	(1.15)	(1.21)	(2.22)	(1.17)	(1.35)	(1.12)	(1.04)	(1.01)	(1.84)
β^{MKT}	0.883	0.882	0.774	0.728	0.776	0.106	0.917	0.989	0.773	0.858	0.839	0.078
β^{HML}	−0.396	−0.106	0.062	0.229	0.177	−0.573	−0.476	−0.255	−0.011	0.159	−0.027	−0.449
β^{SMB}	0.866	0.664	0.627	0.586	0.572	0.293	−0.065	−0.004	0.050	0.162	0.039	−0.104
β^{RMW}	−0.778	−0.440	−0.084	0.090	−0.013	−0.765	−0.062	−0.351	0.166	0.258	0.231	−0.293
β^{CMA}	−0.045	−0.057	0.062	−0.059	−0.066	0.021	0.004	−0.201	0.245	0.052	0.002	0.002

Table C.4 presents unlevered excess returns (α) over a three and a five factor Fama-French model of industry portfolios sorted by quintiles of their elasticity ζ of industry entry to aggregate entry shocks. Returns are unlevered using market leverage and a tax rate of $\tau = 35\%$ such that excess returns are adjusted by $\left(1 + (1-\tau)\frac{\text{Debt}}{\text{Mkt.Cap.}}\right)^{-1}$.

I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), and for five factors the additional profitability (robust minus weak) and investment factor (conservative minus aggressive) all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns. Portfolios returns are either equally weighted (columns (1) to (6)) or value weighted (columns (7) to (12)). Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 1992 to 2017.

Table C.5

Portfolios Sorted on the Elasticity of Industry to Aggregate Entry: η_h — Unlevered Returns

Portfolio quintiles	Low η_h	4	3	2	High η_h	Hi–Lo	Low η_h	4	3	2	High η_h	Hi–Lo
	Average Returns: Equally Weighted						Average Returns: Value Weighted					
	9.43^{***}	10.78^{**}	10.29^{**}	7.64^{**}	7.14^{**}	-2.30^{*}	7.41^{***}	7.03^{**}	6.07	6.12^{**}	5.75^{**}	−1.67
	Fama-French 3 Factor Model: Equally Weighted						Fama-French 3 Factor Model: Value Weighted					
α	1.83	2.37	2.29	−0.13	−0.69	-2.52^{**}	1.46	1.33	−0.40	0.10	−0.73	-2.18^{**}
	(1.36)	(1.78)	(1.77)	(1.15)	(0.898)	(1.06)	(1.04)	(1.09)	(1.19)	(0.895)	(0.862)	(1.08)
β^{MKT}	0.799	0.982	0.971	0.808	0.769	−0.0306	0.794	0.903	1.03	0.785	0.844	0.0506
β^{HML}	0.012	−0.405	−0.425	0.153	0.243	0.232	−0.031	−0.325	−0.445	0.050	0.037	0.068
β^{SMB}	0.689	0.988	0.873	0.551	0.583	−0.105	0.0541	−0.0313	0.0387	0.00391	0.0262	−0.0278
	Fama-French 5 Factor Model: Equally Weighted						Fama-French 5 Factor Model: Value Weighted					
α	2.57^{*}	5.39^{**}	5.76^{***}	0.41	−1.06	-3.63^{***}	0.06	1.47	1.49	−0.28	-2.05^{**}	−2.12
	(1.54)	(2.09)	(1.79)	(1.33)	(1.06)	(1.14)	(1.05)	(1.15)	(0.968)	(0.906)	(0.849)	(1.28)
β^{MKT}	0.772	0.876	0.848	0.787	0.779	0.007	0.848	0.900	0.958	0.800	0.891	0.044
β^{HML}	0.057	−0.255	−0.243	0.190	0.241	0.184	−0.132	−0.327	−0.300	0.018	−0.032	0.100
β^{SMB}	0.654	0.813	0.680	0.528	0.618	−0.036	0.109	−0.047	−0.030	0.016	0.100	−0.009
β^{RMW}	−0.113	−0.535	−0.598	−0.077	0.094	0.207	0.190	−0.041	−0.246	0.046	0.228	0.038
β^{CMA}	−0.040	−0.028	−0.066	−0.040	−0.053	−0.013	0.125	0.031	−0.192	0.048	0.025	−0.100

Table C.5 presents unlevered excess returns (α) over a three and a five factor Fama-French model of industry portfolios sorted by quintiles of their elasticity ζ of industry entry to aggregate entry shocks. Returns are unlevered using market leverage and a tax rate of $\tau = 35\%$ such that excess returns are adjusted by $\left(1 + (1-\tau)\frac{\text{Debt}}{\text{Mkt.Cap.}}\right)^{-1}$.
I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), and for five factors the additional profitability (robust minus weak) and investment factor (conservative minus aggressive) all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns. Portfolios returns are either equally weighted (columns (1) to (6)) or value weighted (columns (7) to (12)). Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 1992 to 2017.

Table C.6

Portfolios based on both ζ_h elasticity and η_h elasticity — Unlevered Returns

Portfolio - ζ_h	High ζ_h			Mid ζ_h			Low ζ_h		
Portfolio - η_h	Low	Mid	High	Low	Mid	High	Low	Mid	High
	Fama-French 3 Factor Model: Equally Weighted								
α	4.829*	2.196	0.165	1.353	0.317	0.074	−0.208	−1.875	−1.143
	(2.56)	(1.96)	(1.4)	(1.3)	(1.61)	(1.18)	(2.25)	(1.33)	(1.27)
β^{MKT}	1.1	1.08	0.709	0.794	0.787	0.8	0.817	0.795	0.871
β^{HML}	−0.557	−0.463	0.171	0.0397	0.318	0.287	0.0809	0.0778	0.276
β^{SMB}	1.15	0.985	0.535	0.692	0.518	0.646	0.612	0.599	0.612
	Fama-French 5 Factor Model: Equally Weighted								
α	9.286***	5.967***	−0.130	1.795	−0.261	−0.633	0.448	−1.106	−1.439
	(2.49)	(2.1)	(1.56)	(1.51)	(1.63)	(1.33)	(2.52)	(1.56)	(1.41)
β^{MKT}	0.931	0.931	0.718	0.776	0.806	0.826	0.786	0.765	0.879
β^{HML}	−0.351	−0.277	0.181	0.0656	0.326	0.263	0.175	0.116	0.3
β^{SMB}	0.898	0.78	0.568	0.67	0.575	0.692	0.619	0.557	0.656
β^{RMW}	−0.766	−0.630	0.087	−0.067	0.153	0.134	−0.016	−0.127	0.109
β^{CMA}	−0.030	−0.064	−0.074	−0.021	−0.111	−0.022	−0.211	−0.015	−0.122
	Fama-French 3 Factor Model: Value Weighted								
α	3.232**	2.243*	0.942	−0.555	1.000	−2.367*	3.998*	−2.939*	0.365
	(1.39)	(1.35)	(1.21)	(0.966)	(1.39)	(1.39)	(2.12)	(1.62)	(1.39)
β^{MKT}	0.958	1.13	0.889	0.853	0.717	0.836	0.732	0.833	0.834
β^{HML}	−0.411	−0.607	−0.0855	0.0929	0.261	0.293	−0.119	0.0855	0.0612
β^{SMB}	0.005	0.135	−0.193	0.121	−0.058	0.166	−0.189	0.017	−0.001
	Fama-French 5 Factor Model: Value Weighted								
α	3.722***	4.251***	0.308	−1.867*	−1.322	−5.076***	1.856	−3.141*	−1.501
	(1.35)	(1.39)	(1.42)	(1.01)	(1.33)	(1.36)	(2.3)	(1.61)	(1.47)
β^{MKT}	0.94	1.05	0.912	0.906	0.811	0.947	0.808	0.84	0.907
β^{HML}	−0.402	−0.436	−0.104	0.0125	0.118	0.108	−0.147	0.0789	−0.0404
β^{SMB}	−0.032	0.076	−0.150	0.181	0.048	0.277	−0.018	0.030	0.094
β^{RMW}	−0.104	−0.226	0.125	0.195	0.343	0.373	0.476	0.039	0.297
β^{CMA}	0.040	−0.268	−0.029	0.073	0.135	0.216	−0.217	−0.007	0.063

Table C.6 presents excess returns (α) over a three and a five factor Fama-French model of industry portfolios double sorted in terciles of their elasticity cash flow elasticity η and of their entry elasticity ζ. Returns are unlevered using market leverage and a tax rate of $\tau = 35\%$ such that excess returns are adjusted by $\left(1 + (1-\tau)\frac{\text{Debt}}{\text{Mkt.Cap.}}\right)^{-1}$.
I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), and for five factors the additional profitability (robust minus weak) and investment factor (conservative minus aggressive) all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns.
Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 1992 to 2017.

Table C.7

Portfolios Sorted on the Elasticity of Industry Entry to Aggregate Entry: ζ

Time Period: 1970-2017

Portfolio quintiles	High ζ_h	4	3	2	Low ζ_h	Hi–Lo	High ζ_h	4	3	2	Low ζ_h	Hi–Lo
	Fama-French 3 Factor Model: Equally Weighted						Fama-French 3 Factor Model: Value Weighted					
α	4.53**	2.22**	0.27	0.33	−1.33	5.86***	3.68***	0.43	0.84	−1.77*	−0.73	4.42***
	(1.92)	(1.06)	(1.35)	(1.09)	(1.11)	(2.12)	(0.886)	(1.12)	(1.27)	(0.896)	(0.896)	(1.42)
β^{MKT}	1.048	1.085	1.007	1.007	1.096	−0.048	0.965	1.079	0.911	1.040	0.987	−0.023
β^{HML}	−0.387	−0.107	0.117	0.330	0.277	−0.663	−0.445	−0.338	0.110	0.267	0.095	−0.541
β^{SMB}	1.191	1.015	0.874	0.840	0.859	0.332	−0.067	0.085	−0.068	0.087	−0.013	−0.054
	Fama-French 5 Factor Model: Equally Weighted						Fama-French 5 Factor Model: Value Weighted					
α	7.89***	4.15***	0.32	−0.20	−1.12	9.01***	3.96***	2.24*	−1.00	−3.35***	−1.43	5.40***
	(1.73)	(1.42)	(1.51)	(1.31)	(1.43)	(1.73)	(0.913)	(1.22)	(1.27)	(0.855)	(0.935)	(1.46)
β^{MKT}	0.984	1.045	1.008	1.015	1.090	−0.105	0.961	1.036	0.961	1.075	1.003	−0.042
β^{HML}	−0.347	−0.053	0.102	0.344	0.299	−0.646	−0.457	−0.238	−0.050	0.206	0.063	−0.520
β^{SMB}	1.008	0.923	0.865	0.877	0.856	0.152	−0.088	0.020	−0.026	0.155	0.015	−0.104
β^{RMW}	−0.756	−0.386	−0.036	0.151	−0.016	−0.740	−0.086	−0.285	0.198	0.291	0.120	−0.207
β^{CMA}	−0.041	−0.098	0.037	−0.042	−0.050	0.008	0.032	−0.210	0.352	0.119	0.065	−0.033

Table C.7 presents excess returns (α) over a three and a five factor Fama-French model of industry portfolios sorted by quintiles of their elasticity ζ of industry entry to aggregate entry shocks. I backfill my elasticity measure at the industry level to estimate portfolio returns over the 1970-2017 period.
I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), and for five factors the additional profitability (robust minus weak) and investment factor (conservative minus aggressive) all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns. Portfolios returns are either equally weighted (columns (1) to (6)) or value weighted (columns (7) to (12)). Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table C.8

Portfolios Sorted on the Firm Cash-Flow Elasticity to Entry: η

Time Period: 1970-2017

Portfolio quintiles	Low η_h	4	3	2	High η_h	Hi–Lo	Low η_h	4	3	2	High η_h	Hi–Lo
	Fama-French 3 Factor Model: Equally Weighted						Fama-French 3 Factor Model: Value Weighted					
α	1.40	2.66*	2.31	0.43	−0.68	−2.08**	0.60	1.25	0.67	0.13	−1.10	−1.70**
	(1.13)	(1.46)	(1.72)	(1.09)	(1.03)	(0.893)	(0.89)	(0.835)	(0.973)	(0.878)	(0.894)	(0.836)
β^{MKT}	1.013	1.072	1.062	1.067	1.034	0.021	0.979	1.002	1.033	0.984	1.029	0.050
β^{HML}	0.112	−0.220	−0.270	0.308	0.276	0.164	−0.081	−0.239	−0.323	0.156	−0.019	0.062
β^{SMB}	0.970	1.115	0.978	0.846	0.857	−0.114	0.090	−0.022	−0.038	0.071	0.036	−0.054
	Fama-French 5 Factor Model: Equally Weighted						Fama-French 5 Factor Model: Value Weighted					
α	1.69	4.98***	5.12***	0.41	−1.01	−2.71***	−0.85	1.16	2.61***	−0.88	−2.39***	−1.54
	(1.4)	(1.64)	(1.7)	(1.3)	(1.3)	(0.951)	(0.876)	(0.873)	(0.851)	(0.814)	(0.781)	(0.964)
β^{MKT}	1.005	1.027	1.004	1.068	1.037	0.032	1.012	1.008	0.989	1.011	1.054	0.043
β^{HML}	0.137	−0.176	−0.191	0.302	0.300	0.163	−0.144	−0.277	−0.233	0.076	−0.043	0.102
β^{SMB}	0.963	0.984	0.831	0.844	0.890	−0.073	0.155	−0.035	−0.121	0.098	0.110	−0.045
β^{RMW}	−0.035	−0.533	−0.604	−0.004	0.128	0.164	0.273	−0.041	−0.353	0.128	0.299	0.026
β^{CMA}	−0.054	−0.052	−0.124	0.014	−0.068	−0.014	0.121	0.093	−0.176	0.173	0.027	−0.094

Table C.8 presents excess returns (α) over a three and a five factor Fama-French model of industry portfolios sorted by quintiles of their elasticity η of cash flow to industry entry. I backfill my elasticity measure at the industry level to estimate portfolio returns over the 1970-2017 period.

I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), and for five factors the additional profitability (robust minus weak) and investment factor (conservative minus aggressive) all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns. Portfolios returns are either equally weighted (columns (1) to (6)) or value weighted (columns (7) to (12)). Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table C.9

Pricing of Risk: Factor mimicking portfolio $\Delta_\zeta R^e$

	A. Standard Time Period: 1990-2017							
	9 portfolios sorted on ζ and η				49 industry portfolios (Fama-French)			
$\Delta_\zeta R^e$|low-η	0.845	0.491		0.423	1.41	0.479		0.595
	(0.337)	(0.289)		(0.355)	(0.275)	(0.263)		(0.281)
R^{MKT}		0.563	−0.483	−0.543		0.92	−0.59	1.08
		(0.363)	(0.583)	(0.592)		(0.232)	(0.485)	(0.247)
R^{HML}			0.0482	0.00878			1.16	−0.195
			(0.412)	(0.428)			(0.366)	(0.237)
R^{SMB}			1.68	1.78			1.45	−0.272
			(0.662)	(0.698)			(0.386)	(0.231)
J-stat	10.3	10.1	4.09	3.88	51.2	46.6	32	44.4
p-value	(0.755)	(0.817)	(0.336)	(0.433)	(0.723)	(0.595)	(0.0892)	(0.586)
	B. Extended Time Period: 1970-2017							
	9 portfolios sorted on ζ and η				49 industry portfolios (Fama-French)			
$\Delta_\zeta R^e$|low-η	0.778	0.428		0.386	1.12	0.384		0.418
	(0.268)	(0.179)		(0.183)	(0.235)	(0.197)		(0.257)
R^{MKT}		0.693	0.397	0.00266		0.875	−0.59	1.21
		(0.27)	(0.401)	(0.43)		(0.212)	(0.485)	(0.253)
R^{HML}			−0.0735	0.355			1.16	−0.189
			(0.297)	(0.367)			(0.366)	(0.209)
R^{SMB}			0.631	0.926			1.45	−0.467
			(0.399)	(0.447)			(0.386)	(0.223)
J-stat	11.6	7.46	8.01	3.98	59.6	53.2	32	45.6
p-value	(0.828)	(0.617)	(0.762)	(0.448)	(0.915)	(0.811)	(0.0892)	(0.635)

The table shows results of estimating the stochastic discount factor of the model ($S = \exp(b_0 - \mathbf{b}'\mathbf{R} - b_X\varepsilon_X)$) via GMM. I report second-stage estimates of $\mathbf{b}$ and b_X using the spectral density matrix. I also report the J-test of over-identifying restrictions and its p-value. Standard errors are in parenthesis.
In Panel A. I estimate the model over the 1990-2017 where we do have entry data. In Panel B. I extend the loadings and estimate the model over the 1970-2017 period.
I use two sets of test assets: 9 industry portfolios sorted in terciles of industry elasticity (ζ) and firm profit elasticity (η); 49 industry portfolios from Ken French's data library (see Fama and French (1997)).
I use the long-short portfolio sorted on the industry elasticity ζ to measure the innovation to entry process. I compare it to the three factor model of Fama and French (1993).

Table C.10

Pricing of Risk: Factor mimicking portfolio $\Delta_\eta R^e$

	A. Standard Time Period: 1990-2017							
	9 portfolios sorted on ζ and η				49 industry portfolios (Fama-French)			
$\Delta_\eta R^e \vert \text{high-}\zeta$	0.767	0.458		0.458	1.17	0.442		0.523
	(0.277)	(0.272)		(0.37)	(0.236)	(0.243)		(0.266)
R^{MKT}		0.572	−0.483	−0.449		0.921	−0.59	1.09
		(0.362)	(0.583)	(0.582)		(0.231)	(0.485)	(0.245)
R^{HML}			0.0482	−0.0889			1.16	−0.266
			(0.412)	(0.443)			(0.366)	(0.24)
R^{SMB}			1.68	1.7			1.45	−0.267
			(0.662)	(0.658)			(0.386)	(0.233)
J-stat	11.4	10.3	4.09	3.52	50.6	46.9	32	44.3
p-value	(0.821)	(0.829)	(0.336)	(0.38)	(0.704)	(0.605)	(0.0892)	(0.585)
	B. Extended Time Period: 1970-2017							
	9 portfolios sorted on ζ and η				49 industry portfolios (Fama-French)			
$\Delta_\eta R^e \vert \text{high-}\zeta$	0.608	0.286		0.271	0.818	0.222		0.236
	(0.222)	(0.152)		(0.147)	(0.193)	(0.188)		(0.246)
R^{MKT}		0.744	0.397	0.402		0.852	−0.737	1.22
		(0.266)	(0.401)	(0.405)		(0.205)	(0.437)	(0.244)
R^{HML}			−0.0735	−0.113			1.24	−0.315
			(0.297)	(0.333)			(0.357)	(0.207)
R^{SMB}			0.631	0.64			1.53	−0.529
			(0.399)	(0.411)			(0.354)	(0.225)
J-stat	14.3	9.29	8.01	7.88	59.8	55.1	33.4	47.1
p-value	(0.925)	(0.767)	(0.762)	(0.837)	(0.882)	(0.804)	(0.0837)	(0.613)

The table shows results of estimating the stochastic discount factor of the model ($S = \exp(b_0 - \mathbf{b}'\mathbf{R} - b_X \varepsilon_X)$) via GMM. I report second-stage estimates of $\mathbf{b}$ and b_X using the spectral density matrix. I also report the J-test of over-identifying restrictions and its p-value. Standard errors are in parenthesis.
In Panel A. I estimate the model over the 1990-2017 where we do have entry data. In Panel B. I extend the loadings and estimate the model over the 1970-2017 period.
I use two sets of test assets: 9 industry portfolios sorted in terciles of industry elasticity (ζ) and firm profit elasticity (η); 49 industry portfolios from Ken French's data library (see Fama and French (1997)).
I use the long-short portfolio sorted on the industry elasticity ζ to measure the innovation to entry process. I compare it to the three factor model of Fama and French (1993).

Table C.11

Summary Statistics based on Terciles of Concentration

	Concentration Terciles		
	High	Mid	Low
Concentration Ratio (Census)	82.8	62.3	37.5
Herfindahl Index (Census)	556.3	275.6	80.8
Concentration Ratio (Compustat)	61.9	64.8	82.8
Markups Level (%)	20.9	31.8	25.5
Markups Volatility (%)	21.7	20.4	15.4
Industry Elasticity η	-0.920	-1.067	1.004

Table C.11 presents industry statistics by terciles of concentration from the *Census of Manufactures* of the U.S. Census Bureau.
The measures of concentration are the 50 firms concentration ratio at the four-digit NAICS level and the Herfindahl-Hirschman for the 50 largest companies from the *Census of Manufactures.* Measures of markups, levels and volatilities, and the profit elasticity η are the same as in the main summary statistics Table **??** from the paper.

Table C.12

Portfolios based on both ζ_h elasticity and cash flow risk

ζ_h-sort	High ζ_h			Mid ζ_h			Low ζ_h		
	Panel A: Cash-Flow Elasticity: η_h								
	Low η	Mid	High η	Low η	Mid	High η	Low η	Mid	High η
α	5.563**	3.625*	0.820	1.663	0.087	0.571	0.117	−1.960	−1.083
	(2.635)	(2.081)	(1.702)	(1.641)	(2.098)	(1.667)	(2.702)	(2.007)	(1.642)
β^{MKT}	1.200	1.160	0.865	0.973	1.028	1.010	1.005	1.134	1.097
β^{HML}	−0.530	−0.463	0.248	0.146	0.483	0.410	0.193	0.221	0.379
β^{SMB}	1.224	1.079	0.698	0.851	0.680	0.807	0.773	0.748	0.815
	Panel B: Concentration ratio (Census)								
	High CR	Mid	Low CR	High CR	Mid	Low CR	High CR	Mid	Low CR
α	7.597***	6.783***	4.828**	1.440	4.473***	3.520**	−4.402*	0.095	1.518
	(2.751)	(2.415)	(2.261)	(1.917)	(1.670)	(1.486)	(2.636)	(3.238)	(1.682)
β^{MKT}	1.060	1.185	1.051	1.021	0.964	0.941	1.133	1.113	0.956
β^{HML}	−0.490	−0.423	−0.245	0.516	0.084	0.353	0.586	0.304	0.284
β^{SMB}	1.146	1.074	1.091	0.590	0.868	0.826	0.572	0.743	0.813
	Panel C: Herfindahl-Hirschman Index (Census)								
	High HHI	Mid	Low HHI	High HHI	Mid	Low HHI	High HHI	Mid	Low HHI
α	8.959***	6.480**	1.298	3.911**	2.066	3.888**	−10.270***	3.175	−0.936
	(3.141)	(2.706)	(1.935)	(1.597)	(2.174)	(1.806)	(3.843)	(4.139)	(2.826)
β^{MKT}	1.213	1.039	1.126	0.959	1.037	0.953	1.394	1.057	1.128
β^{HML}	−0.339	−0.439	0.201	0.281	0.173	0.248	0.879	0.560	0.697
β^{SMB}	0.996	1.149	0.942	0.654	0.959	0.786	0.908	0.625	0.914
	Panel D: Markups μ_h								
	High μ_h	Mid	Low μ_h	High μ_h	Mid	Low μ_h	High μ_h	Mid	Low μ_h
α	8.376***	6.508**	4.896**	2.814	1.131	5.381***	0.599	1.850	−1.415
	(2.923)	(2.646)	(2.056)	(1.936)	(1.646)	(1.799)	(1.973)	(2.140)	(2.337)
β^{MKT}	0.981	1.202	1.104	1.018	0.968	0.945	1.075	1.012	1.029
β^{HML}	−0.395	−0.466	−0.374	0.498	0.377	0.068	0.419	0.431	0.277
β^{SMB}	1.181	1.099	1.028	0.707	0.737	0.895	0.720	0.831	0.697

Table C.12 presents excess returns (α) over a three factor Fama-French model of industry portfolios double sorted in terciles of their elasticity cash flow risk and of their entry elasticity ζ_h. Cash flow risk is measured by the cash flow elasticity η_h in panel A, concentration ratio (from the Census) in panel B, Herfindahl index in panel C and average markups in panel D.
I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low) all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns.
Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 1992 to 2017.

Table C.13

Hi—Lo Portfolios based on both ζ_h elasticity and cash flow risk

Panel A: Cash-Flow Elasticity: η_h

Portfolio Sort	Hi –Lo η_h			Hi –Lo ζ_h		
	High ζ_h	Mid ζ_h	Low ζ_h	Low η_h	Mid η_h	High η_h
α	4.743*	1.092	1.200	5.446*	5.586**	1.903
	(2.466)	(1.173)	(1.788)	(3.207)	(2.178)	(1.741)
β^{MKT}	0.335	−0.037	−0.092	0.195	0.025	−0.233
β^{HML}	−0.778	−0.264	−0.186	−0.723	−0.684	−0.131
β^{SMB}	0.526	0.044	−0.041	0.451	0.332	−0.117

Panel B: Concentration ratio (Census)

Portfolio Sort	Hi –Lo CR			Hi –Lo ζ_h		
	High ζ_h	Mid ζ_h	Low ζ_h	High CR	Mid CR	Low CR
α	2.769	−2.080*	−5.920**	11.999***	6.689*	3.310
	(2.143)	(1.212)	(2.716)	(3.439)	(3.436)	(2.508)
β^{MKT}	0.009	0.080	0.177	−0.073	0.073	0.094
β^{HML}	−0.244	0.163	0.303	−1.076	−0.726	−0.529
β^{SMB}	0.055	−0.236	−0.241	0.575	0.331	0.278

Panel C: Herfindahl-Hirschman Index (Census)

Portfolio Sort	Hi –Lo HHI			Hi –Lo ζ_h		
	High ζ_h	Mid ζ_h	Low ζ_h	High HHI	Mid HHI	Low HHI
α	7.661***	0.023	−9.334**	19.229***	3.518	2.234
	(2.745)	(1.742)	(4.333)	(4.603)	(4.851)	(3.145)
β^{MKT}	0.087	0.006	0.266	−0.181	−0.022	−0.002
β^{HML}	−0.540	0.033	0.182	−1.217	−0.998	−0.496
β^{SMB}	0.053	−0.133	−0.006	0.088	0.525	0.028

Panel D: Markups μ_h

Portfolio Sort	Hi –Lo μ_h			Hi –Lo ζ_h		
	High ζ_h	Mid ζ_h	Low ζ_h	High μ_h	Mid μ_h	Low μ_h
α	3.480	−2.567	2.014	6.311**	4.658	7.777**
	(2.598)	(1.724)	(1.951)	(2.655)	(3.000)	(2.961)
β^{MKT}	−0.123	0.073	0.046	0.075	0.189	−0.094
β^{HML}	−0.022	0.430	0.142	−0.651	−0.897	−0.814
β^{SMB}	0.153	−0.187	0.023	0.330	0.268	0.461

Table C.13 presents excess returns over a three factor Fama-French model of long short industry portfolios double sorted in terciles of their elasticity cash flow elasticity η_h and of their entry elasticity ζ_h. In column (1) to (3), I present portfolios that are long high cash flow risk and short low cash flow risk, for different terciles of their industry entry elasticity ζ_h. Cash flow risk is measured by the cash flow elasticity η_h in panel A, concentration ratio (from the Census) in panel B, Herfindahl index in panel C and average markups in panel D. In column (4) to (6), I present portfolios that are long high industry entry elasticity ζ_h and short small ζ_h, for different terciles of their cash flow elasticity.
I regress a given portfolio's return in excess of the risk-free rate on the market portfolio minus the risk-free rate, the size factor (small minus big), the value factor (high minus low), all obtained from Kenneth French's website. Monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns.
Standard errors are estimated using Newey-West with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is 1992 to 2017.