Capital Depreciation and Industry Competition: Theory and Evidence

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Abstract

We argue that the rate of capital depreciation is a determinant of competition, measured using markups. We develop a general equilibrium model of industry competition where industries vary in their rate of capital depreciation. In equilibrium, optimal savings decisions imply that rapid depreciation is related to higher costs of capital, so that industries with rapid depreciation display less competition than industries with slow depreciation. We then show that the rate of capital depreciation has a robust positive relationship with market power in US data. The calibrated model accounts for most of the observed dispersion in markups across US industries.

JEL Codes: E2, D2, D4, L1

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1 Introduction

Competition in product markets is a fundamental source of macroeconomic efficiency. As a result, extensive research explores the fundamental determinants of industry competition and the implications of rising market power in recent years.[1] However, Schmalensee (1989) underlines that there are significant and persistent differences in competition *across industries*. Cross industry-variation in markups is quantitatively important: while De Loecker et al. (2020) find that markups vary between 21% and 61% from 1980 to 2016, we find that the 10th percentile industry markup value over the same period is 5%, while the 90th percentile is 95%.Understanding the technological factors underlying these persistent differences could be as important as understanding changes over time, both for our understanding of competition and for the appropriate design of industrial or anti-trust policy.

In this paper we argue that *the rate of capital depreciation* could be a technological determinant of cross-industry differences in competition. Our reasoning is as follows. Consider an endogenous general equilibrium investment model, extended to have two types of capital – distinguished by their depreciation rate. Optimal investment would require the net interest rate on both types of capital to be the same, so that the *gross* interest rate on capital with a higher depreciation rate is higher. In turn, this entails a higher cost of capital for firms in industries that require capital that depreciates more rapidly. Given higher costs, fewer firms could profitably operate in the industry, which implies less competition and higher markups in such industries in equilibrium.

[1] See De Loecker et al. (2020), Autor et al. (2020), Berry et al. (2019), Acemoglu and Hildebrand (2017), Faccio and Zingales (2017) and Barkai (2016)

To articulate our intuition, we develop a general equilibrium model of oligopoly with many industries. Industries differ in the depreciation rate of the capital they use. In each industry there is a finite number of firms engaged in non-cooperative Cournot competition. Firms exit stochastically, and are replaced at a cost if it is profitable to do so. Even though there is an integer number of firms in each industry, there is a continuum of industries with a different equilibrium number of firms in each, so that labor demand can be continuous and so aggregate variables can vary continuously with parameters. We show that the household's investment problem implies that industries with rapid depreciation face a higher cost of capital, because the household's optimal investment decision requires a higher interest rate for more rapidly depreciating capital. As a result, those industries are able to support fewer firms in equilibrium. In this way, the depreciation-competition link could be seen as a natural prediction of standard models of investment, once they are extended to allow for oligopolistic competition as here.

Next, we explore whether US industry data support a depreciation-competition link. We measure competition using markups, as in De Loecker et al. (2020). Then, we relate industry rates of capital depreciation to industry markups at the 4-digit North American Industry Classification System (NAICS) level, both in cross-section and using a time panel. We use panel data because cross-sectional correlations could be influenced by omitted factors. In particular, it could be that capital depreciation is correlated with other technological variables – see Samaniego and Sun (2020). Panel data, on the other hand, allow us to condition on factors that might be correlated with depreciation over the long-run. Thus, we employ industry fixed effects in a series of regressions on a panel of US firms with markups on the left hand side and depreciation, along with industry control variables and time dummies, on the right hand side. We find that industries with higher rates of capital depreciation indeed display higher markups, as hypothesized.

For robustness, we identify other technological variables that could be correlated with depreciation or that might otherwise be potentially related to industry competition. For this purpose, we begin with a standard definition of "technology", using it as a guide for choosing variables that measure "technological" differences across industries. As is standard in growth theory, we define "technology" in terms of the production function: the way in which factors of production are arranged, combined and converted into outputs. Hence, we measure industry differences in technology using factor intensities, or using the qualitative attributes of factors of production – an approach dating back at least to Cobb and Douglas (1928). Aside from capital depreciation, the variables we consider are Research & Development intensity (R&D), asset fixity and investment lumpiness, as well as advertising expenditure. High R&D expenditures, advertising expenditures, a high degree of asset fixity or high investment lumpiness are likely to be associated with high fixed or variable costs. Nonetheless, we do not find any link between competition and any of the other technological characteristics, nor does conditioning on any of these technological variables weaken the relationship between depreciation and competition.

Finally, we calibrate the model economy to US industry depreciation rates. We find that, for reasonable parameterizations, the correlation between markups in the model and the data is highly statistically significant. In addition, the *magnitude* of the depreciation-competition link in the model – in the form of a regression coefficient – is close to the coefficient in the empirical exercise. Under these parameters, the model also accounts for almost the full cross-sectional variation in industry markups found in the data. The variance of markups is also similar to that in the data. We conclude the model is able to account both for the magnitude and most of the cross-sectional variation in markups seen in the data.

As an application of our model, we study the impact of cross-country differences in entry costs in a model with imperfect competition. We find that the impact of entry costs is substantial, consistent with other studies. However, we also show that imperfect competition is key to the impact of entry costs, as high entry costs endogenously decrease competition and reduce the volume of entry, which reduces the incidence of entry costs. If we hold the number of firms constant and ignore the impact of entry costs on competition, the impact of entry costs turns out to be far greater.

Our paper contributes to the literature on the variations in market power and determinants of industry competition. The literature defines market power in two ways: (i) the markup of price over marginal cost, and (ii) concentration (Syverson 2019). Although concentration ratios e.g. the Herfindahl-Hirshman Index (HHI) are sometimes used to measure market power, recent studies have pointed out various issues with concentration measures such as their sensitivity to the definition of the market (De Loecker et al. 2020). As a result, in this paper, we focus on markups as a well-established proxy for market power to examine industry competition.

The survey of Schmalensee (1989) develops stylized facts on industry concentration through intra-industry studies using cross-sectional data, underlining the importance of extending this literature to panel data and inter-industry studies which would enable the study of long-run differences across industries and robust relationships that hold across large samples of markets. Additionally, panel data are more useful for our purposes as cross-sectional data may be difficult to interpret due to the possibility of omitted variables (e.g. that could be accounted for using fixed effects in panel data). We implement this methodology to investigate technological characteristics as potential determinants of industry competition, using panel data and markups as a robust measure of market power.

We build on recent studies such as Autor et al. (2020), Council of Economic Advisors (2016) and De Loecker et al. (2020), who look at changes in the level of competition across industries in the U.S. over time. We follow De Loecker et al. (2020) in calculating markups at the firm level following the production approach, based on Hall (1988) and De Loecker and Warzynski (2012), and then use the average markup for each 4-digit North American Industry Classification System (NAICS) industry in each year to measure industry competition. Instead of focusing on how the general trend of rising markups relates to other macroeconomic trends, we focus on identifying the underlying technological variables that drive the variation in markups *across industries*.

The literature on the determinants of competition has focused on R&D spending, advertising expenditures (Sutton 2007; Schmalensee 1989; De Loecker et al. 2020; Acemoglu and Hildebrand 2017; Corhay et al. 2020) and capital deepening (Autor et al. 2020), since they affect product creation, returns to investment and thus can create incumbent advantages for high market shares and productive firms. We focus instead on a new determinant of competition – the rate of capital depreciation – as growth theoretic considerations suggest it could be important. As a result, our paper also contributes to our understanding of investment models which underpin the standard growth model. In a world of imperfect competition, we show that a standard model of investment decisions predicts a depreciation-competition link. We show empirically that this link exists in the data, and show that a canonical model of oligopoly in combination with a standard intertemporal investment decision can quantitatively account for much of the variation in markups.

The rest of our paper proceeds as follows. Section 2 features the descriptions of our model and Section 3 presents the solutions to the model, to flesh out the intuition linking depreciation rates with competition. In Section 4, we present our empirical methodology. Section 5 presents the estimation results. We calibrate the parameters of the model to match the data in Section 6. Section 7 presents quantitative findings from the model. Section 8 concludes our paper.

2 Economic Environment

Time is discrete. There exists a $[0, 1]$ continuum of differentiated goods, each produced by a different industry.

Each industry comprises a *finite* number of firms, who engage in non-cooperative Cournot price competition. There is a separate capital accumulation equation for each industry. Industries $j \in [0, 1]$ differ in terms of the depreciation rate δ_j of the capital that they use. We assume that depreciation rates range continuously within some interval $\left[\underline{\delta}, \overline{\delta}\right]$ and are increasing in j without loss of generality. Let $F(\cdot)$ be the cumulative distribution function describing the distribution of δ_j across industries.

There is a holding company that owns firms and starts new ones. The holding company is free to start new firms in any industry if it is profitable to do so. Thus, all industries are contestable. If it creates a measure ϵ_t of new firms at date t, it must pay an entry cost $c_e \epsilon_t$ in units of labor.

Finally, a word on interpretation. There are millions of firms in the United States, yet clearly there is market power and concentration. We interpret the model as assuming a large number of identical localities, with few firms in each industry and locality. Alternatively we could interpret the model at the national level, where each industry may have a few large players with a fringe of small firms which we do not model as they do not in general account for a significant proportion of output.

2.1 Households

Households have one unit of labor each period, which they supply to a competitive labor market in exchange for a wage w_t. Households also earn income by renting capital to the industries at rate r_{jt} for each industry j. Finally, they also earn income $\Pi_t(\cdot)$ from the holding company, which collects profits from all the firms.

Households use their income to purchase the final good. The final good, however, has two uses: consumption $\mathbf{c}_t$, and investment i_{jt} in capital for any industry $j \in [0, 1]$. Industries differ in terms of the depreciation rate δ_j of the capital they use.

Let $\mathbf{k}_t : [0, 1] \to \mathbb{R}^+$ be a function that represents the stock of capital in each industry $j \in [0, 1]$, and let $\mathbf{c}_t$ be the agent's consumption in units of the final good.

The household's problem is then:

$$
\begin{aligned}
V(\mathbf{k}_t, \mu_t) &= \max_{\mathbf{c}_t, \mathbf{k}_{t+1}, \epsilon_t} \left\{ u(\mathbf{c}_t) + \beta V(\mathbf{k}_{t+1}, \mu_{t+1}) \right\} \qquad (1) \\
& s.t \\
k_{j,t+1} &= (1-\delta_j) k_{jt} + i_{jt} \ \forall j \in [0,1] \\
P_t \mathbf{c}_t + P_t \int i_{jt} dj &= w_t (1 - c_e \epsilon_t - \kappa \mu_t) + \int r_{jt} k_{jt} dj + \Pi(\mu_t).
\end{aligned}
$$

where the utility function $u(\cdot)$ is strictly increasing and concave. Here μ_t is the measure of firms owned by the household, and $\Pi(\mu_t)$ equals any profits generated by firms. We defer a discussion of how μ_t evolves over time and how μ_{t+1} is affected by ϵ_t until later. The measure μ_t can be thought of as a firm registry: see Samaniego (2010).

The final good is a composite of the goods produced by the various industries. Let y_{jt} be total use of good $j \in [0,1]$. The final good $\mathbf{y}_t$ is an aggregate of all the goods, according to the following constant-elasticity production function:

$$
\mathbf{y}_t = \left(\int_0^1 y_{jt}^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}}.
$$

The parameter σ is the elasticity of substitution across goods.

We will assume the households are symmetric as our focus is on competition and on heterogeneity among industries.

2.2 *Producers*

Each industry j has a finite number of firms, which engage in non-cooperative Cournot competition each period. The firms' production function is

$$y_{ht} = z k_t^{\alpha} l_t^{1-\alpha}$$

where h indexes the firm, y_{ht} is its output of good j, k_t is the capital it rents at date t and l_t is its labor input.

Firms take the wage w_t and interest rate r_{jt} as given, and maximizes discounted profits. The firm's value function is:

$$V_h\left(\widehat{Y}_{-ht}|j\right) = \max_{k_t \geq 0, l_t \geq 0} \left\{ y_{ht} p(y_{ht}, \widehat{Y}_{-ht}) - w_t l_t - r_j k_t - w_t \kappa + \beta \left(1 - \delta_f\right) V_h\left(\widehat{Y}_{-h,t+1}|j\right) \right\}, \tag{2}$$

where $\widehat{Y}_{-ht}$ is the output of the firms in the industry *other than* firm h, $p(y_{ht}, \widehat{Y}_{-ht})$ is the inverse demand function faced by the firm – which depends both on the output of firm h and that of its competitors – and κ is a fixed cost of operation, paid in terms of labor. Firms break down exogenously at rate δ_f at the beginning of each period, so $V_h\left(\widehat{Y}_{-ht}|j\right)$ is the value of a firm that has already found it is continuing into period t. Let l_h^* and k_h^* index the optimal labor and capital choice respectively.

Problem (2) is static, so in much of what follows we will suppress time subcripts where this does not cause confusion. Nonetheless the value function $V_h\left(\cdot\right)$ will be important as it will matter later for entry decisions.

2.3 Entry

Households may produce a firm at cost c_e in terms of labor. It will be profitable to do this if the entry of an additional firm is such that the expected profits $V_h\left(\widehat{Y}_{-h}\right)$ exceed the cost $c_e w_t$. In equilbrium, this will occur if a firm closes in one of the industries. The number of firms closing in any particular industry is a random variable: however if the total measure of firms is μ_t then it is known that the measure of closing firms is $\delta_f \mu_t$. Thus in equilibrium it will be that

$$\delta_f \mu_t = \epsilon_t.$$

We will focus on equilibria where all firms behave symmetrically, so that $\widehat{Y}_{-h} = (N_j - 1)\, y_h$. This implies that $V_h\left(\widehat{Y}_{-h}|j\right)$ is will be decreasing in the number of firms in equilibrium. Optimal entry then implies that, in all industries, the number of firms N_j is such that

$$V_h\left(\widehat{Y}_{-h}|j\right) \geq c_e w_t$$

and, for $N_j + 1$

$$V_h\left(\widehat{Y}_{-h}|j\right) < c_e w_t.$$

2.4 Equilibrium

We study a stationary, symmetric equilibrium in this environment (henceforth "equilibrium"), defined as a measure μ, a level of consumption $\mathbf{c}$ and a mapping $N : [0,1] \to \mathbb{N}^*$, investment choices i_{jt} price functions $p_j(\cdot)$ and choices l_h^* and k_h^* for each firm in all industries such that:

1. Households solve problem (1);
2. Firms solve problem (2);
3. Entry decisions are optimal, i.e. there are no expected profits to be earned by additional entry into any industry;
4. The number of firms in each industry j, $N(\delta_j)$, does not change over time;
5. Firms in any given industry j chose the same values of l_h^* and k_h^*;
6. Markets clear for all goods j, all types of capital j and for labor, so that, if I_j is the set of firms in industry j

$$\begin{aligned}\sum_{h \in I_j} y_h &= y_j \ \forall j, \\ \sum_{h \in I_j} k_h^* &= k_j \ \forall j, \\ \int l_h^* d\mu &= 1 - c_e \epsilon - \kappa\mu.\end{aligned}$$

Notice that there is no requirement that there be symmetry *across* industries. Industry asymmetry is an essential component of the model as it allows us to study variation in concentration across industries.

3 Model solution

3.1 Final goods market

We begin by focusing on the problem of optimal composition of $\mathbf{y}_t$. We will find it convenient to write the budget constraint as

$$\int_0^1 p_j y_j dj = I.$$

where I is household income. Households solve the following problem each period

$$\max_{\{y_j\}} \left(\int_0^1 y_j^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}} s.t. \int_0^1 p_j y_j dj = I, \ \sigma > 1.$$

It is straightforward to show that:

Proposition 1. *The demand function for good j is represented by:*[2]

$$Y_j^d = \left(\frac{p_j}{P}\right)^{-\sigma} I, \tag{3}$$

where P_t equals the price index of the composite price $\mathbf{y}_t$, which is:

$$P_t \equiv \left(\int_0^1 p_{jt}^{1-\sigma} dj \right)^{\frac{1}{1-\sigma}}.$$

Proof. All proofs are collected in Appendix C. ■

[2] See Appendix C.

Without loss of generality we henceforth set $P_t = 1$, so the aggregate final good is also the numeraire good.

The household's problem simplifies to

$$V\left(\mathbf{k}_t, \mu_t\right) = \max_{\mathbf{k}_{t+1}} \left\{ u\left(w_t\left(1 - \epsilon_t - \kappa\mu_t\right) + \int r_{jt}k_{jt}dj - \int \left[k_{j,t+1} - \left(1-\delta_j\right)k_{jt}\right]dj \right) + \beta V\left(\mathbf{k}_{t+1}, \mu_{t+1}\right) \right\}$$

The following FOC with $k_{j,t+1}$must hold for almost all j:

$$u'\left(\mathbf{c}_t\right) = \beta u'\left(\mathbf{c}_{t+1}\right)\left[r_{j,t+1} + 1 - \delta_j\right]$$

Notice that, since consumption is constant over time in equilibrium, this implies that:

Proposition 2. *Industries with higher depreciation rates experience a higher cost of capital, in the form of a higher rental rate.*

$$r_{jt} = \beta^{-1} - 1 + \delta_j.$$

This is a straightforward consequence of the household's intertemporal investment decision.

Consider a particular industry j and firm h. From the sectorial demand equation (3), it follows that firm h faces an inverse demand given by

$$y_h\left(p_{j,}\widehat{Y}_{-h}\right) = p_j^{-\sigma}I - \widehat{Y}_{-h} \tag{4}$$

where $\widehat{Y}_{-h}$ is production by all firms in industry j other than firm h, which it takes as given. Rearranging, we have the inverse demand function:

$$p_j\left(y_h, \widehat{Y}_{-h}\right) = \left(\frac{y_h + \widehat{Y}_{-h}}{I}\right)^{\frac{-1}{\sigma}}. \quad (5)$$

As a Cournot oligopolist, the firm chooses its output realizing that its output together with the output of all other firms in the sector determine their price p_j.

Denote by $\varepsilon_{hj} \equiv -\frac{\partial y_h}{\partial p} \cdot \frac{p}{y_h}$ the elasticity of demand faced by firm h. It is straightforward to show that $\varepsilon_{hj} = \sigma\left(y_h + \widehat{Y}_{-h}\right)/y_h$: the firm-level elasticity of demand is inversely proportional to that firm's share of sectorial output. Denoting by s_{hj} that share, we have that

$$\varepsilon_{hj} = \frac{\sigma}{s_{hj}}.$$

Thus a larger firm faces a smaller elasticity of demand for its own product. Consequently, if firms are the same size, the elasticity of substitution will be related to their number N_j since $s_{hj} = 1/N_j$. In that case, we have that:

Proposition 3. *In equilibrium, the price elasticity of demand is strictly increasing in the number of firms N_j:*

$$\varepsilon_j = \sigma N_j.$$

Thus, the intensity of concentration in the model economy is increasing in N_j.

Define $\pi_j(N)$ as the profits of a firm in industry j assuming there are N firms. It is straightforward to show that

Proposition 4. *In equilibrium, $\pi_j(N)$ is decreasing in N.*

From Proposition 2, it follows that:

Proposition 5. *In equilibrium, $N(\delta_j)$ is a lower-hemicontinuous step function that is weakly decreasing in δ_j.*

Proposition 5 implies that competition is more intense in industries with low values of δ_j, *ceteris paribus.* To see this, note that the markup η_j in industry j in te Cournot model is

$$\eta_j = \frac{1}{1 - 1/\varepsilon_j}$$

Combining this with Proposition 5, our primary empirical prediction follows:

Proposition 6. *In equilibrium, markups are weakly increasing in δ_j.*

Proposition 6 is a direct consequence of the oligopolistic structure of the model economy and the fact that rapid depreciation raises the cost of capital. In an oligopolistic environment this results in the fact that firms in industries with rapid depreciation will, in equilibrium, support fewer firms and thus experience less intense competition.

It is not in general possible to prove existence in this model. One obstacle is that the entry cost c_e would need to be sufficiently small for entry to be profitable. The other is the fact that the number of firms in any industry N_j is an integer. As a result, if the range of depreciation values $\left[\underline{\delta}, \overline{\delta}\right]$ is too narrow then aggregate labor demand may not be continuous. Nonetheless, we can characterize the construction of the equilbrium, which provides an algorithm for its computation.

First, take w and I as given. Using equation (5) the firm's static profits $\pi\left(\widehat{Y}_{-h}|j\right)$

can be written

$$\pi\left(\widehat{Y}_{-h}|j\right)=\max_{k,l}\left\{zk^{\alpha}l^{1-\alpha}\left(\frac{zk^{\alpha}l^{1-\alpha}+\widehat{Y}_{-h}}{I}\right)^{\frac{-1}{\sigma}}-wl-r_jk-w\kappa\right\}. \tag{6}$$

The first order conditions are:

$$p(l)y_l+yp'(y)y_l=w, \tag{7}$$

and

$$p(l)y_k+yp'(y)y_k=r_j. \tag{8}$$

Further derivations show that

$$p'(y)=\frac{-1}{\sigma}\frac{1}{I}\left(\frac{y+\widehat{Y}_{-k}}{I}\right)^{\frac{-1-\sigma}{\sigma}},$$

and

$$y_l=(1-\alpha)\,y/l,\ y_k=\alpha y/k.$$

Now suppose that in the industry there are $N_j\in\mathbb{N}^*$ firms. If within industries all firms are identical then (7) and (8) respectively imply that

$$(1-\alpha)\,(y)^{\frac{\sigma-1}{\sigma}}\left[\left(\frac{N}{I}\right)^{\frac{-1}{\sigma}}-\frac{1}{\sigma}\frac{1}{I}\left(\frac{N}{I}\right)^{\frac{-1-\sigma}{\sigma}}\right]=wl, \tag{9}$$

and

$$\alpha\,(y)^{\frac{\sigma-1}{\sigma}}\left[\left(\frac{N}{I}\right)^{\frac{-1}{\sigma}}-\frac{1}{\sigma}\frac{1}{I}\left(\frac{N}{I}\right)^{\frac{-1-\sigma}{\sigma}}\right]=r_jk. \tag{10}$$

These combine to determine the optimal capital-labor ratio $\tilde{k}$:

$$\tilde{k}_j \equiv \frac{k_j^*}{l_j^*} = \frac{w\alpha}{r_{j(1-\alpha)}}. \tag{11}$$

Replacing this into (9) we obtain

$$l_j^* = w^{-\sigma}\left[z^{\frac{\sigma-1}{\sigma}}(1-\alpha)\left(\frac{w\alpha}{r_{j(1-\alpha)}}\right)^{\alpha\frac{\sigma-1}{\sigma}}\left[\left(\frac{N}{I}\right)^{\frac{-1}{\sigma}}-\frac{1}{\sigma}\frac{1}{I}\left(\frac{N}{I}\right)^{\frac{-1-\sigma}{\sigma}}\right]\right]^{\sigma} \tag{12}$$

Thus, given values of w and I and N, we can compute l_j^* and k_j^*. Then, if $y^*(N)$ is the output produced by a firm when there are N firms present, then

$$\pi\left(\widehat{Y}_{-h}|j\right) = \pi\left((N-1)\,y^*(N)\,|j\right) - w_t\kappa$$

and

$$V_h\left(\widehat{Y}_{-h,t+1}|j\right) = \pi\left((N-1)\,y^*(N)\,|j\right) \div \left(1-\beta\left(1-\delta_f\right)\right)$$

Using this, in each industry we find the optimal number of firms using:

$$N^*(\delta_j) = \max\left\{N \in \mathbb{N}^* : V_h\left((N-1)\,y^*(N)\,|j\right) \geq c_e w\right\}.$$

Define

$$\mathbf{N} = \left\{N \in \mathbb{N}^* : \exists\delta \in \left[\underline{\delta}, \overline{\delta}\right] \text{ with } N = N(\delta_j)\right\}.$$

Proposition 7. *In equilibrium, there exists a decreasing function $\Delta^* : \mathbf{N} \to \mathbb{R}^+$ such that the number of firms in the industry is at least $N \in \mathbb{N}^*$ if $\delta \leq \Delta^*(N)$. For* *values of* $\Delta^*(N)$ *in the interior of* $\left[\underline{\delta}, \bar{\delta}\right]$, $\Delta^*(N)$ *is continuous in* w.

So far we have assumed a value for w, and a guess of income I. We assume capital markets clear using Walras' law: given $N^*(\delta_j)$ and k_j^* we can compute the total capital of each tyle. Then, it should be clear that l_j^* is strictly decreasing in w in all industries and that N is weakly decreasing in w. Thus labor demand is strictly decreasing in w. To see this, note that labor demand is

$$\begin{aligned} L_d &= \int l_j^* N^*(\delta_j)\, dF(\delta) \\ &= \sum_{N \in \mathbf{N}} \int l_j^* N \times \mathbf{1}\left[\Delta^*(N+1) < \delta \leq \Delta^*(N)\right] dF(\delta) \end{aligned}$$

where $\mathbf{1}$ is the indicator function. In equilibrium L_d must be continuous in the wage as $\Delta^*(N)$ is continuous in the wage. Labor supply is

$$L_s = 1 - c_e \epsilon - \kappa \mu.$$

The total mass of firms is

$$\begin{aligned} \int d\mu_t &= \int N^*(\delta_j)\, dF(\delta_j) \\ &= \sum_{N \in \mathbf{N}} \int N \times \mathbf{1}\left[\Delta^*(N+1) < \delta \leq \Delta^*(N)\right] dF(\delta) \end{aligned}$$

so that

$$\epsilon = \delta_f \mu.$$

As we raise w we lower the labor demand of each firm, and also lower the number of firms, so L_d is strictly decreasing in w between zero and infinity. Lowering the number of firms lowers ϵ, also between zero and infinity, so the labor supply is weakly increasing, so given I there must be a wage that clears the labor market. This could be a candidate wage as long as c_e is not so high that entry is not profitable in the first place: then there would be no firms (the L_d curve should be truncated at some point where entry is not profitable).

Finally, let I_n be our initial guess of income I. Having used it to derive the model decision rules, we can compute income implied by this guess, which is

$$I_{n+1} = w_t \left(1 - c_e \epsilon - \kappa \mu\right) + \int r_{jt} k_{jt} dj + \Pi\left(\mu_t\right).$$

We solve for equilibrium by using I_{n+1} as a new guess, and iterating on the above procedure until $\|I_{n+1} - I_n\| < \varepsilon$ for some tolerance level ε.

Finally, assuming we have found an equilibrium, we can show that

Proposition 8. *If $\Delta^*(N)$ is in the interior of $\left[\underline{\delta}, \bar{\delta}\right]$, the value of $\Delta^*(N)$ is continuous in parameters.*

This implies that the equilibrium value of I will be continuous in parameters as well. The model thus allows us to have an integer number of firms in each industry and endogenous rents while having a continuous response of aggregates to policy variables. This is a useful result as it implies that the model framework is suitable for policy experiments. We will illustrate this potential later by calibrating the model and studying the impact of entry costs on aggregates.

4 Estimation Method and Data

In this section we proceed to test empirically the key prediction of the model – that depreciation rates should be linked to competition.

A simple way to see whether depreciation is related to competition is by assembling cross-sectional data on the two variables and comparing them with each other. However, while useful, any such findings would be largely suggestive, as omitted variables – including technological variables other than depreciation – could be responsible for any significant correlations.

As a result, following Schmalensee (1989), we turn to panel data in order to exploit *time variation* in depreciation (as well as other technological variables) and competition. Specifically, to test for potential determinants of industry competition, we adopt the fixed effects panel regression approach. Let Mu_{jt} be the measure of competition for industry j, which is proxied by the industry's average markup of price over marginal cost. Let $Tech_{jt}$ be the measure of a technological characteristic for industry j and $Controls_{jt}$ represent control variables that are explained in section 4.2. Let d_j and T_t denote industry and year fixed effects. We estimate the following equation:

$$Mu_{jt} = \beta_0 + Tech_{jt} + Controls_{jt} + d_j + T_t + \epsilon_{jt} \tag{13}$$

In specification 13, all time- and industry-specific factors affecting industry concentration are removed by the fixed effects. The four technological characteristics that we investigate include depreciation rate, R&D intensity, investment lumpiness and asset fixity.

We use the Compustat database of financial, statistical and market information on active and inactive companies in the United States from 1961 (the first year when all our variables of interest become available) to 2016. Compustat provides detailed firm-level output and input information over a substantial period of time, which enables us to calculate and construct a comprehensive panel of markups, advertising intensity and technological variables.

We use three different measures of markup: the main measure Mu_2 backed out from a standard Cobb Douglas production function with time-varying technological parameters, which is used in parallel with our time-invariant measure (Mu_1) and another markup measure (Mu_3) backed out from an alternative production function that includes overhead costs as robustness checks for our results. Our calculation method for markups follows De Loecker et al. (2020) and is presented in Appendix D.

4.1 Technological Characteristics

We explore four potential technological determinants of market power in this paper. The first of course is our variable of main interest, capital depreciation rate (DEP). However, we will also use several other technological variables as controls: asset fixity (FIX), R&D intensity (R&D) and investment lumpiness (LMP).

The reason we select these variables is as follows. As we show later, rapid depreciation is related to higher costs of capital, which could lower profits for a given degree of competition, leading to less competition in equilibrium. Asset fixity should be related to the capital share of output which could be related to higher startup costs. R&D intensity has been thought of in the literature as a proxy for high fixed costs. Investment lumpiness is linked in Samaniego (2010) with high adjustment costs.

For each of the five technological variables, we first calculate the variable itself at the firm level. Then, for DEP, FIX, R&D and LMP, we take the mean of each variable for each industry in each year. We use industry codes at the 4-digit NAICS level for all sectors in the United States.

We make the assumption that capital markets in the United States, especially for publicly listed firms, are relatively frictionless, so that using these data allows us to identify an industry's technological characteristics (or technological demand for external financing).

The measures for asset fixity (FIX_{jt}), capital depreciation rate (DEP_{jt}) and R&D intensity (RND_{jt}) follow Samaniego and Sun (2015). Investment lumpiness (LMP_{jt}) is defined as in Ilyina and Samaniego (2011) as the average number of investment spikes experienced by Compustat firms in a given industry over a given period of time, in this case over every five year period.

The formula to measure each variable is defined as follows:

(i) Asset fixity is equal to the ratio of fixed assets (PPENT) to total assets (AT).

(ii) Depreciation is measured as ratio of the value of depreciation (DP) to the value of property, plant and equipment (PPENT).

(iii) R&D intensity is measured as R&D expenditures (XRD) over total capital expenditures (CAPX).[3]

(iv) Investment lumpiness is defined as the average number of investment spikes experienced by firms in each industry while an investment spike is defined as an annual capital expenditure (CAPX) exceeding 30% of the firm's total assets stock (AT). LMP_{jt} is thus a dummy variable that takes on the value of 1 if the ratio of annual capital expenditure to fixed assets is equal to or greater than 0.3. We take the mean of this variable for each industry to represent the technological characteristic of investment lumpiness for the industry in that year.

Table 1 presents some summary statistics of the key variables at the firm level including markups and technological characteristics as well as control variables including advertising (XAD) and industry share of employment (EMP). We exclude from the dataset the top and bottom 1 percent of firm observations in terms of the cost of goods sold to sales ratio which is calculated for each year separately. We winsorize each technological variables except for LMP (as this is a dummy variable) at 1% and 99% levels to minimize the impact of outliers. In addition, we eliminate firm observations belonging to an unspecified sector (coded as 99 at the 2 digit level) and values of DEP that are greater than 1 since these are possibly due to measurement errors. In Appendix A, we conduct robustness checks in with the dataset winsorized up to 3% of top and bottom values, and our results are robust to these alternative winsorized datasets. As we can see, average firm markup (Mu_2) is quite high at

[3] It is common to measure R&D intensity as a ratio of sales. However, Ngai and Samaniego (2011) argue against the use of this measure as the denominator (sales) may be directly affected by markups by construction, arguing for cost-based measured as in Ilyina and Samaniego (2011) instead.

1.61 or 61% above marginal costs.

Table 1: **Summary Statistics (1961-2016)**

Variable	Acronym	Mean	Median	Nr Obs
Sales	SALE	2,143,964	160,174	346,576
Cost of Goods Sold	COGS	1,474,482	95,667	346,576
Capital Stock	PPEGT	1,923,113	65,739	313,410
Overhead (SG&A)	XSGA	355,306	29,235	276,693
Employment (No. of People)	EMP	7,904	800	299,659
Total Assets	AT	6,198,175	232,414	346,447
Property, Plant and Equipment	PPENT	1,052,836	34,055	340,300
Capital Expenditures	CAPX	177,617	6,559	322,133
Advertising Expenses	XAD	60,036	1,656	111,054
Depreciation Value	DP	119,281	5,446	333,066
R&D Expenditures	XRD	79,536	2,560	149,585
Firm Markup (Time-Invariant, PF1)	Mu_1	1.75	1.34	346,576
Firm Markup (Time-Varying, PF1)	Mu_2	1.61	1.26	346,575
Firm Markup (Time-Varying, PF2)	Mu_3	1.30	1.03	346,575
Capital Depreciation Rate	DEP	0.20	0.15	16,512
R&D Intensity	RND	0.08	0.01	11,830
Investment Lumpiness	LMP	0.07	0	17,230
Asset Fixity	FIX	0.33	0.29	17,159

Notes: Financial variables are reported in thousands USD, deflated using GDP Deflator with base year 2012 (Deflator data obtained from FRED[a]038¡p type="texpara" tag="Body Text" ¿https://fred.stlouisfed.org/series/GDPDEF0). For technological variables, industry means and medians are reported. For other variables, firm-level means and medians are reported.

[a]

Table 2 shows pairwise correlations between the markup measures and technological characteristics as well as advertising expense (XAD). As we can see, the three markup measures are highly correlated with each other. Meanwhile, DEP, RND and LMP are consistently, significantly and positively correlated with all three markup measures. XAD is positively and significantly correlated with two out of three markup measures while the sign of the correlation coefficient of FIX is negative with Mu_1 and positive with Mu_3. As we can see from the later panel regression results, however, most of these raw correlations fade under the application of industry and time fixed effects.

Table 2: **Pairwise Correlations of Markup and Technological Variables**

	Mu_1	Mu_2	Mu_3	DEP	RND	LMP	FIX	XAD
Mu_1	1							
Mu_2	0.9782*	1						
Mu_3	0.9536*	0.9739*	1					
DEP	0.1306*	0.0893*	0.0712*	1				
RND	0.1325*	0.0959*	0.0974*	0.2617*	1			
LMP	0.0446*	0.0612*	0.0656*	-0.1074*	-0.0094	1		
FIX	-0.0303*	0.0125	0.0188*	-0.4844*	-0.1164*	0.0869*	1	
XAD	0.0189*	0.0137	0.0191*	-0.0137	0.0028	-0.0510*	-0.0248*	1

**$p<0.05$*

Table 3 below shows the mean/median value of the technological characteristics for each of the 22 U.S. sectors (at 2-digit NAICS) across the time period of our analysis.

Table 3: **Technological Characteristics by Sector (1961-2016)**

NAICS	Sector	RND	FIX	LMP	DEP
11	Agriculture, Forestry, Fishing & Hunting	0.094	0.444	0.057	0.104
21	Mining, Quarrying, Oil & Gas Extraction	0.025	0.645	0.173	0.13
22	Utilities	0.038	0.745	0.155	0.05
23	Construction	0.019	0.236	0.076	0.195
31	Manufacturing (1)	0.018	0.292	0.029	0.159
32	Manufacturing (2)	0.104	0.321	0.03	0.185
33	Manufacturing (3)	0.087	0.228	0.029	0.234
42	Wholesale Trade	0.015	0.202	0.037	0.215
44	Retail Trade (1)	0.002	0.315	0.032	0.166
45	Retail Trade (2)	0.007	0.262	0.028	0.194
48	Transportation & Warehousing (1)	0.02	0.616	0.088	0.109
49	Transportation & Warehousing (2)	0.026	0.413	0.05	0.186
51	Information	0.159	0.267	0.043	0.309
52	Finance & Insurance	0.023	0.046	0.338	0.219
53	Real Estate & Rental & Leasing	0.023	0.364	0.093	0.17
54	Professional, Scientific & Technical Services	0.12	0.169	0.032	0.351
56	Admin., Waste Mgt & Remediation Services	0.053	0.236	0.037	0.289
61	Educational Services	0.078	0.242	0.034	0.266
62	Healthcare & Social Assistance	0.036	0.304	0.038	0.239
71	Arts, Entertainment, & Recreation	0.015	0.536	0.072	0.126
72	Accommodation & Food Services	0.001	0.589	0.102	0.123
81	Other Services (except Public Administration)	0.037	0.288	0.04	0.204

Notes: FIX (asset fixity), DEP (depreciation), LMP (investment lumpiness), and RND (R&D intensity) are represented by the mean value of all firms in a sector. Median value across firms in a sector is shown for EFD (external finance dependence). Sector codes follow the North American Industry Classification System (NAICS) at the 2-digit level.

4.2 Control Variables

As part of specification 13, the vector of control variables $Controls_{jt}$ includes the average advertising expenditure and the industry's employment as share of total employment of all industries. The reason we include advertising is that it is viewed as a potential determinant of competition in the literature, so we wish to ensure our findings are robust to conditioning on advertising. The reason we include the share of employment is to control for the possibility that industry size might be related to competition – which might be related to preferences or the stage of development, neither of which are strictly technological. Finally, we also condition on time dummies and on industry fixed effects, to account for any time varying factors that might affect competition across the board, or for any fixed industry characteristics affecting competition.

5 Empirical Results

Tables 4, 5, 6 and 7 show the regression results for each of the technological variables (DEP, RND, LMP, and FIX) with Mu_1 (time invariant, sector-specific, PF1), Mu_2 (time varying, sector-specific, PF1), and Mu_3 (time-varying, sector-specific, PF2) as markup measures, respectively. For these regressions we have excluded outlier values of DEP (those that are greater than 1) as well as those of markups (top 1%) to avoid having outliers drive the results. Advertising expense is scaled to unit of US$ to make sure the magnitude of its coefficient is not too small to show in the result tables.

As we can see from these tables, the results are economically significant for DEP as it has consistently positive and significant coefficients across the regressions with three different measures of markup. An increase of 10 percentage points in capital depreciation rate raises markup by 1.43 percentage points (Mu_2 measure). Since the median markup (Mu_2) is 26% over marginal costs, this is a significant change. Meanwhile, we do not obtain significant results for other technological characteristics (FIX, RND and LMP). These results make a strong case for DEP as a determinant of market power in industries.

Table 4: **Markups and Capital Depreciation**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
Depreciation	0.220***	0.143***	0.088**
	(0.057)	(0.050)	(0.040)
Advertising	0.091*	0.078*	0.071**
	(0.048)	(0.047)	(0.034)
Employment share	-1.049	-0.332	-0.252
	(1.209)	(1.022)	(0.752)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	10889	10892	10901

Robust standard errors in parentheses, clustered at the industry level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: **Markups and R&D Intensity**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
R&D	-0.001	-0.007	0.013
	(0.032)	(0.029)	(0.022)
Advertising	0.083*	0.073	0.066**
	(0.050)	(0.047)	(0.032)
Employment share	-1.581	-0.550	-0.090
	(1.444)	(1.116)	(0.929)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	9863	9869	9884

Robust standard errors in parentheses, clustered at the industry level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Interestingly, despite demonstrated links between R&D intensity and competition in the literature, we do not find support for that notion, possibly indicating either no link or a non-linear link.[4]

[4]As Aghion et al. (2005) find an inverted U-shaped relationship between innovation and compe-

Table 6: **Markups and Investment Lumpiness**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
Investment lumpiness	-0.075	-0.046	-0.001
	(0.054)	(0.058)	(0.044)
Advertising	0.097**	0.078*	0.076**
	(0.049)	(0.046)	(0.033)
Employment share	-1.551	-0.605	-0.339
	(1.383)	(1.105)	(0.792)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	11338	11345	11358

Robust standard errors in parentheses, clustered at the industry level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: **Markups and Asset Fixity**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
Asset fixity	-0.128	-0.051	-0.040
	(0.116)	(0.108)	(0.082)
Advertising	0.096**	0.077*	0.076**
	(0.048)	(0.046)	(0.033)
Employment share	-1.471	-0.561	-0.330
	(1.284)	(1.068)	(0.774)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	11335	11342	11355

Robust standard errors in parentheses, clustered at the industry level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix A shows our robustness checks with the regressions repeated on different versions of the dataset that are trimmed up to 3% of top and bottom values of the ratio of cost of goods sold to sales. The sign and significance of the coefficient of

tition, we test this relationship by including the square of R&D intensity in Appendix B and find no supporting evidence. They measure competition using the HHI index. As a result, it is not clear that their findings necessarily will be reflected in markups. Our findings concerning depreciation are robust to using HHIs instead of markups: these results are available upon request.

Table 8: **Horse Race with All Technological Variables as Controls**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
Depreciation	0.180***	0.127**	0.071*
	(0.057)	(0.053)	(0.042)
R&D	−0.021	−0.020	0.004
	(0.035)	(0.031)	(0.024)
Investment lumpiness	−0.038	0.007	0.0480
	(0.053)	(0.050)	(0.044)
Asset fixity	0.011	0.038	0.023
	(0.143)	(0.131)	(0.099)
Advertising	0.081	0.076	0.063*
	(0.049)	(0.047)	(0.033)
Employment share	−1.215	−0.378	−0.055
	(1.307)	(1.085)	(0.895)
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	9460	9461	9472

Robust standard errors in parentheses, clustered at the industry level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

DEP remain robust across these winsorized datasets. We conclude that depreciation is a new potential determinant of competition that deserves further exploration.

Finally, in Table 8 we verify the robustness of the coefficient on DEP to controlling for all the technological variables by including them in the same specification. Although the statistical significance is a little weaker, with Mu_3 as the measure of markups, the overall results remain unchanged.

6 Calibration

We now calibrate the model economy with two purposes in mind. One is to see whether the quantitative link between depreciation and concentration in the model economy is similar to that in the data. The other is to showcase the suitability of the model for policy analysis.

The model economy has a continuum of industries with continuously distributed depreciation rates. However in the data we will have only a finite number of industries. We will thus have to solve for equilibrium approximately in the sense that one of the equilibrium conditions will not hold exactly. The risk is that as we vary I to find the equilibrium the number of firms N in some industry jumps, leading to a lack of continuity. However we find that in practice this does not occur.[5]

The parameters we require are a set of industries, a list of depreciation rates δ_j for each industry, an exit rate δ_f, an entry cost c_e, a discount rate β, a capital share α, a productivity term z and an elasticity parameter σ.

First of all, we normalize $z = 1$. Then we set $\beta = 0.947$ and $\alpha = 0.3$, which are standard values in the literature. Samaniego (2010) finds that 12.6 percent of establishments close each year, so we set $\delta_f = 0.126$.

We use the same set of 400+ industries as in our empirical study, and set the value of δ_j equal to the value in the data for each one.

[5]This is likely because we have so many industries that any errors due to jumps are insignificant. If this were not the case the solution would be to define a stepwise distribution of δ_j that fits the data, and then use a continuous approximation to that distribution.

We use several values of σ. Anderson and Van Wincoop (2004) find that in the trade literature estimates of σ around 5 or higher are common. However non-tradeables may be different. Ilyina and Samaniego (2012) find an elasticity of around 3.75 in manufacturing data, and Samaniego and Sun (2019) find a value of σ around 1.3. We will explore values in the range $[1.3, 5]$.

Djankov et al. (2002) find that the cost of entry in the US is about one percent of GDP, so we set $c_e = 0.01$.

Finally, we select κ so as to match the median markup in the data, which is 1.0691 based on the markup measure that allows for time-varying parameters. This will be matched by the median industry, which has a value of δ_j of 21.3 percent. It remains to see whether variation in δ_j can lead to reasonable variation in model markups.

7 Quantitative Findings

We start by exploring the strength of the interaction between depreciation and concentration in the model economy.

If η_j is the model markup for industry j and δ_j is the depreciation rate, Figure 1 plots the coefficient $\hat{\beta}$ obtained by estimating the equation $\eta_j = \alpha + \hat{\beta}\delta_j + \epsilon_j$. We find that the relationship depends on our assumptions about σ. When we assume $\sigma = 3.3$, about the estimate in Ilyina and Samaniego (2012), this coefficient turns out to be around 0.13, close to the coefficient in our preferred specification (Mu_2, with time varying coefficients). In this sense, the model and the data are consistent with each other when σ is around the higher end of the values we explore.

It turns out that for all values of σ the correlation between markups in the model and the data is highly significant (around 0.1, significant at the 1 percent level). However, a more pertinent measure of goodness of fit is the value of a regression coefficient with model markups on the RHS and the data on the LHS. If this coefficient is large, it means the model is underpredicting the variation in markups in the data. If the coefficient is unity, it means the model-generated variation matches that in the data. Thus, the inverse coefficient is more directly indicative of whether the model under- or over-predicts the variation in the data. The lower panel Figure 1 displays the magnitude of the inverse coefficient for different values of σ. When $\sigma = 3.33$, the inverse coefficient is about 0.71, so that the model is able to account for over two thirds of the variation in markups in the data. The coefficient equals unity around $\sigma = 3.65$.

Another way to see whether the model is generating reasonable variation in markups is to compare the standard deviation of markups in the model with that in the data. In the data the cross-sectional standard deviation is 0.298, a value the model satisfies when $\sigma = 3.4$ – see Figure 2. In this sense, the model economy is able to account for most or all of the empirical variation in markups solely on the basis of variation in depreciation rates, when σ is in the range $3.3 - 3.7$.

Next, we ask what is the impact of entry costs in the model. The size and spectrum of entry costs has made their aggregate impact a topic of interest since at least De Soto (1989). However, the only general equilibrium studies that examine the aggregate impact of entry costs are Barseghyan and DiCecio (2011) and Moscoso-Boedo and Mukoyama (2012), models that do not have a notion of con-

Figure 1: Top panel: Regression coefficient in the model economy, as a function of the elasticity of substitution. The regression is $\eta_j = \alpha + \hat{\beta}\delta_j + \epsilon_j$ where η_j is the model-generated markup and $\hat{\beta}$ is the coefficient on depreciation. Bottom panel: magnitude of markups in the model compared to the data. The magnitude is the inverse of the coefficient $\hat{\beta}$ in a regression $\hat{\eta}_j = \alpha + \hat{\beta}\eta_j + \epsilon_j$ where $\hat{\eta}_j$ is the markup in the data. A small inverse coefficient means the model markups η_j are much smaller than those in the data. An inverse coefficient of one means the variation in model-generated markups is similar to that in the data.

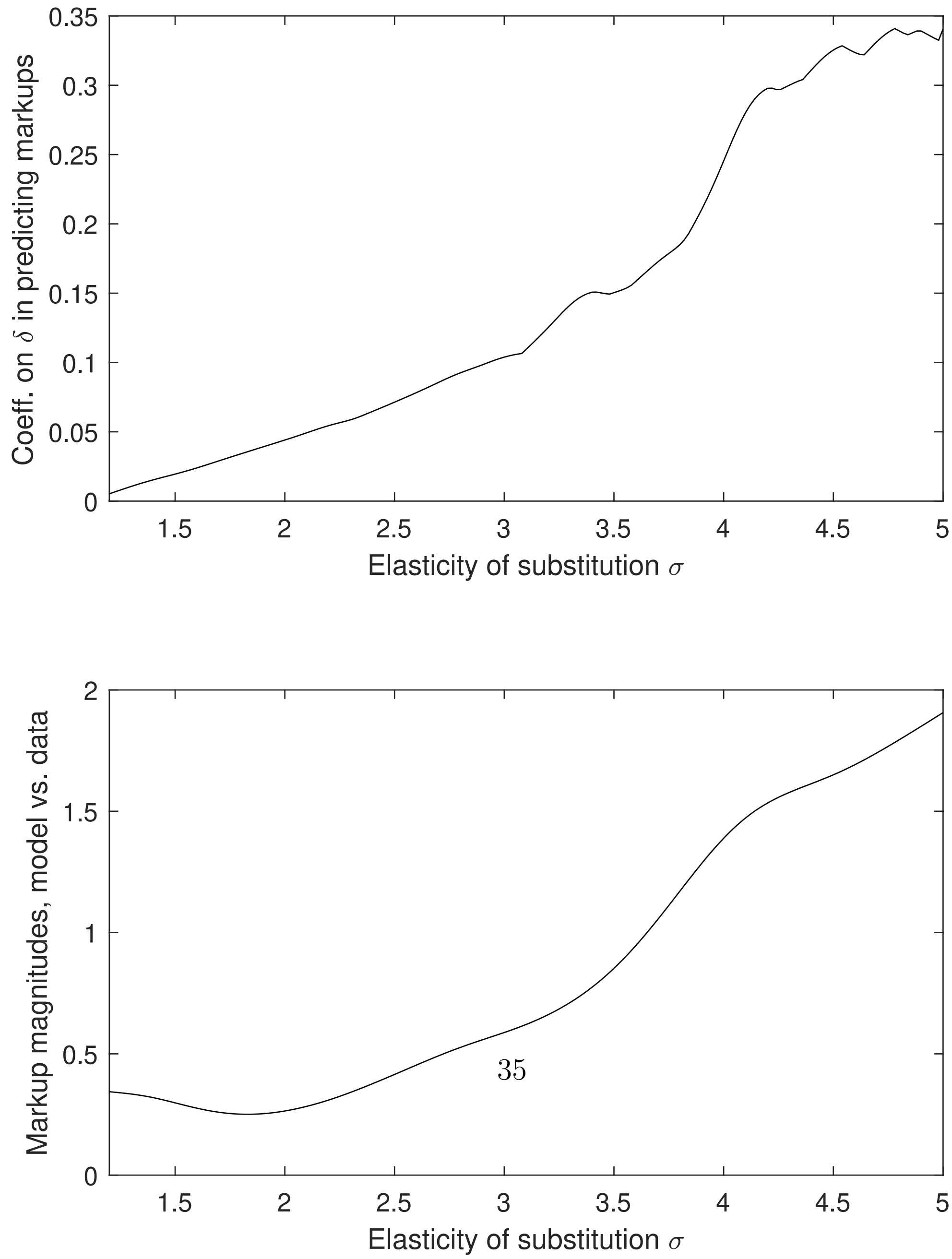
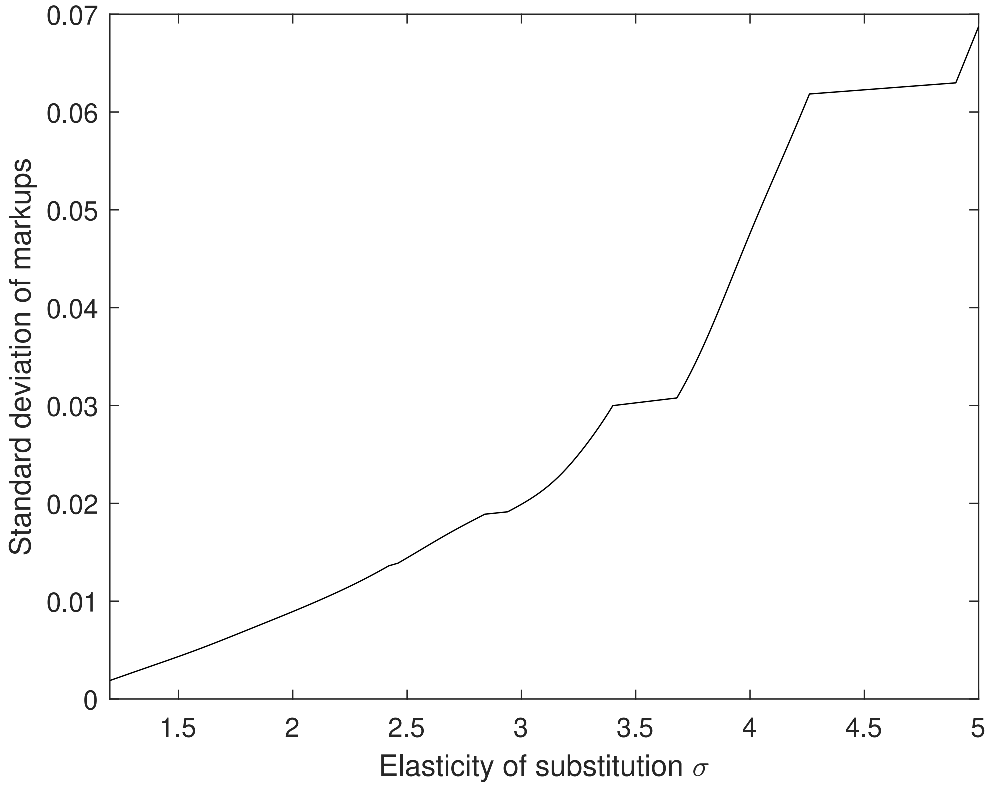


Figure 2: Standard deviation of model-generated markups.



centration. Samaniego (2010) shows that entry costs affect rates of entry and exit disproportionately in industries with certain technological characteristics – particularly investment-specific technical change, which can be shown to be related to depreciation rates because economic depreciation is faster where new capital is becoming productive at an increasing rate: however, the firms in Samaniego (2010) are infinitesimal. Thus, the literature has not addressed how entry costs might affect concentration in general equilibrium.

To study the link between entry costs and concentration, we set $\varepsilon = 3.5$, in the middle of the $3.3 - 3.7$ range that appear most empirically relevant.

Our experiment is to vary entry costs relative to the baseline. This raises the question as to what is the empirically relevant range for changing entry costs. Moscoso-Boedo and Mukoyama (2012) document that in the US formal entry costs are very small, about 1 percent of the wage. Thus, the US can be used as a useful benchmark. On the other hand, in some countries they find that entry costs are several times the wage, e.g. around 1000 times in the case of Sierra Leone. However, unlike them, we do not believe that this implies that, for example, in the case of Sierra Leone we should believe that c_e is 1000 times higher than in the US ($c_e = 100$). The reason is that these high entry costs could occur for two reasons. One is that entry costs might be enormous in Sierra Leone. The other is that wages are low in Sierra Leone for other reasons, such as low productivity for reasons unrelated to entry costs.[6] In particular, it is well known that institutions and regulations tend to be "bundled"

[6]See Gollin (2008) regarding caution about leaping to conclusions about the causality between policy and outcomes in developing economies.

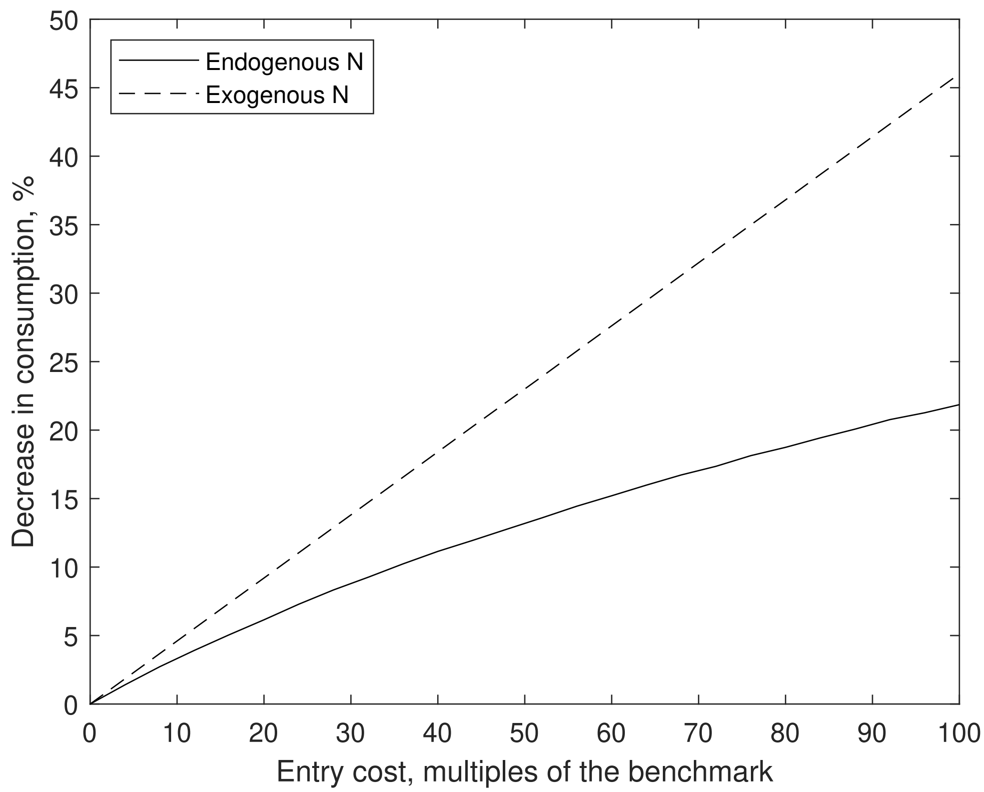
together – see Acemoglu and Johnson (2005) and Samaniego (2013) – so the high entry costs in Sierra Leone are likely correlated with other institutional features that could hamper economic development (or the absence of certain features that might support development). Thus one cannot measure the aggregate effect of entry costs of an empirically relevant magnitude by simply matching the range of entry costs relative to wages around the world.

Consider that the GDP per capita of the United States has been about 100 times that of Sierra Leone on average since 1990, according to the World Bank. This implies that if there were no differences in entry costs but some *other* factor led GDP in Sierra Leone to be low, entry costs relative to wages would be 100 times higher in Sierra Leone than in the US. Moscoso-Boedo and Mukoyama (2012) report that (relative to wages) in Sierra Leone entry costs are about 1000 times larger, i.e. three orders of magnitude. That suggests that a conservative estimate of the empirically relevant range of entry costs is up to $1000/10 = 10$ times the US value. This suggests we should consider values in the range $c_e \in [0.01, 0.1]$, rather than $c_e \in [0.01, 10]$. As a compromise we explore the range $c_e \in [0.01, 1]$, so entry costs may vary by a factor of one hundred (rather than ten or one thousand).

Figure 3 displays the aggregate impact of the increase in entry costs, measured as the percentage decline in consumption. We find that entry costs of empirically relevant magnitude have a substantial impact on economic welfare in the model economy, reducing consumption in steady state by up to 22 percent. This is seen in the line labeled "Endogenous N".

Figure 4 also shows that entry costs have a substantial impact on markups. While

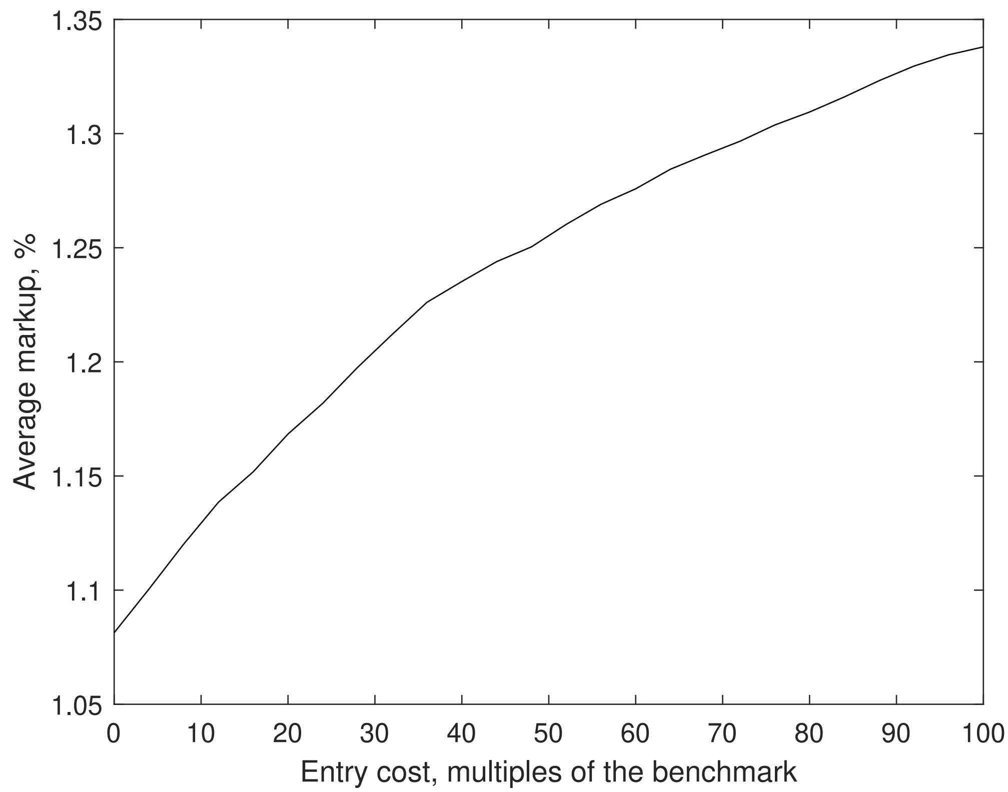
Figure 3: Relationship between entry costs and the percentage decrease in consumption in the model economy – or, alternatively, the compensating variation of reducing the entry costs to the benchmark level. The horizontal axis is c_e, the entry costs relative to wages. The vertical axis is the compensation variation



the average markup in the benchmark economy is about 1.08, it increases steadily with entry costs, reaching about 1.34 when $c_e = 1$.

This decline in concentration turns out to be important for the aggregate impact of entry costs. To see this, we repeat the experiment of raising entry costs, however we do not allow the number of firms to vary relative to the baseline. In other words, even though it may not be profitable to have the same number of firms when c_e is raised, we keep the number of firms in each industry equal to that in the baseline economy. The dashed line labeled "Exogenous N" in Figure 3 shows that in this economy the impact of entry costs is even greater, with consumption declining by up to 46 percent. Instead, when entry is endogenous, the higher entry costs result in decreased concentration, which also means that the volume of firms paying entry costs declines as entry costs rise. This is related to De Soto (1989), where high entry costs decrease welfare not only because agents are forced to pay them but because of the avoidance behavior it induces. In our case, it involves reduced entry, which also results in less concentration. In De Soto (1989), it involves an expansion of the informal sector, something that would be useful to study in an extension of our framework.

Figure 4: Entry costs and competition in the model economy. The horizontal axis represents the % increase in the entry cost above the benchmark. The vertical axis is the average markup in the model economy



8 Conclusion

In this paper, we propose a link between competition and depreciation as a natural consequence of standard general equilibrium models of investment, when extended to allow for oligopolistic competition. We do so in the context of a general equilibrium model economy with many industries with different depreciation rates. We then show that depreciation is indeed related to competition in US panel data, as well as in cross-section. We use markups to proxy for market power, and use panel data to circumvent the limitations of cross-sectional data to uncover the determinants of cross-industry variation in markups.

The calibrated model accounts for almost the full variation in markups across industries even assuming that all firms in a given industry are identical. It would be interesting to extend the model in the future to allow for different firm sizes and richer industry dynamics to see what factors might allow depreciation to account for more of the cross-sectional variation in markups. At the same time, empirical work to uncover further potential determinants of markup variation would also be useful.

Finally, information and communications technologies are forms of capital that experience relatively rapid depreciation and which have comprised an increasing share of investment in recent decades. Given recent interest in trends in markups, it would be interesting to see whether an increase in rates of depreciation *over time* might account for some portion of the recently observed upward trend in markups found by De Loecker et al. (2020).

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Appendices

A Robustness Checks

This Appendix shows our robustness checks with datasets trimmed up to 3% of top and bottom values of the ratio of cost of goods sold to sales. We run the same regressions for each markup measure over each of the technological variables (DEP, RND, LMP and FIX) across four different versions of the dataset as shown below. The sign and significance of the coefficient of DEP remain robust across these winsorized datasets.

A.1 Dataset Winsorized at 2% Level

Table 9: **Markups and Capital Depreciation**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
Depreciation	0.191***	0.128***	0.080**
	(0.048)	(0.045)	(0.035)
Advertising	0.089*	0.078*	0.072**
	(0.046)	(0.046)	(0.032)
Employment share	-1.009	-0.288	-0.202
	(1.169)	(1.001)	(0.738)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	10878	10880	10879

Robust standard errors in parentheses, clustered at the industry level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: **Markups and R&D Intensity**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
R&D	0.027	0.014	0.033
	(0.043)	(0.039)	(0.028)
Advertising	0.083*	0.073	0.066**
	(0.048)	(0.046)	(0.031)
Employment share	-1.968	-1.024	-0.431
	(1.693)	(1.311)	(1.007)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	9823	9825	9832

Robust standard errors in parentheses, clustered at the industry level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: **Markups and Investment Lumpiness**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
Investment lumpiness	-0.032	0.006	0.023
	(0.052)	(0.047)	(0.037)
Advertising	0.092*	0.076*	0.074**
	(0.047)	(0.045)	(0.032)
Employment share	-1.781	-0.828	-0.472
	(1.538)	(1.231)	(0.845)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	11306	11311	11318

Robust standard errors in parentheses, clustered at the industry level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: **Markups and Asset Fixity**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
Asset fixity	-0.065	0.006	-0.011
	(0.097)	(0.093)	(0.068)
Advertising	0.091*	0.076*	0.075**
	(0.047)	(0.045)	(0.032)
Employment share	-1.744	-0.834	-0.485
	(1.488)	(1.236)	(0.840)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	11303	11308	11315

Robust standard errors in parentheses, clustered at the industry level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.2 Dataset Winsorized at 3% Level

Table 13: **Markups and Capital Depreciation**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
Depreciation	0.171***	0.115***	0.064**
	(0.041)	(0.040)	(0.031)
Advertising	0.046	0.036	0.035
	(0.028)	(0.027)	(0.025)
Employment share	-0.768	-0.089	-0.149
	(1.017)	(0.855)	(0.632)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	10853	10853	10857

Robust standard errors in parentheses, clustered at the industry level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: **Markups and R&D Intensity**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
R&D	0.032	0.024	0.050
	(0.046)	(0.041)	(0.030)
Advertising	0.043	0.033	0.032
	(0.029)	(0.025)	(0.023)
Employment share	-1.469	-0.743	-0.292
	(1.286)	(1.056)	(0.814)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	9762	9766	9776

Robust standard errors in parentheses, clustered at the industry level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15: **Markups and Investment Lumpiness**

	(1)	(2)	(3)
	Mu_1	Mu_2	Mu_3
Investment lumpiness	-0.016	-0.003	0.025
	(0.044)	(0.041)	(0.034)
Advertising	0.051*	0.036	0.040
	(0.030)	(0.027)	(0.025)
Employment share	-1.295	-0.575	-0.388
	(1.239)	(1.050)	(0.720)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	11261	11268	11279

Robust standard errors in parentheses, clustered at the industry level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 16: **Markups and Asset Fixity**

	(1)	(2)	(3)
	Mu_1	Mu_2	Mu_3
Asset fixity	-0.040	0.031	0.011
	(0.081)	(0.077)	(0.058)
Advertising	0.050*	0.037	0.040
	(0.030)	(0.027)	(0.025)
Employment share	-1.274	-0.580	-0.408
	(1.208)	(1.073)	(0.727)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	11258	11265	11276

Robust standard errors in parentheses, clustered at the industry level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Verifying the U Shape Relationship between Innovation and Competition

We include the square of R&D in our regressions to verify the potential U shape relationship between innovation and competition according to Aghion et al. (2005). We find no evidence of this relationship as shown in Table 17 below.

Table 17: **Markups and the Square of R&D Intensity**

	(1)	(2)	(3)
	Mu_1	Mu_2	Mu_3
R&D	-0.001	-0.006	0.014
	(0.033)	(0.030)	(0.022)
Square of R&D	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Advertising	0.082*	0.073	0.066**
	(0.049)	(0.047)	(0.032)
Employment share	-1.554	-0.550	-0.089
	(1.440)	(1.116)	(0.929)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	9864	9869	9884

Robust standard errors in parentheses, clustered at the industry level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C Model's Proofs

Proof of Proposition 1. The household solves hte static problem

$$\max_{\{c_{j,n}\}} \left(\int y_j^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}},$$
$$s.t. \ \int p_j y_j dj = I,$$

where p_j is the price of good j and I the income of the household. Optimality requires that the following first order condition hold almost everywhere:

$$y_j^{\frac{\sigma-1}{\sigma}-1}\left(\int y_j^{\frac{\sigma-1}{\sigma}}dj\right)^{\frac{\sigma}{\sigma-1}-1}=\lambda p_j$$

or

$$y_j^{\frac{-1}{\sigma}}\mathbf{y}^{\frac{1}{\sigma}}=\lambda p_j$$

Raising both sides to the power of $1-\sigma$ we obtain that

$$y_j^{\frac{\sigma-1}{\sigma}}\mathbf{y}^{\frac{1-\sigma}{\sigma}}=\lambda^{1-\sigma}p_j^{1-\sigma}.$$

Integrating both sides over j we obtain

$$\lambda^{1-\sigma}\int p_j^{1-\sigma}dj=1.$$

Finally defining the price index for consumption as P (i.e. the shadow price of consumption in terms of income), we obtain that

$$P\equiv 1/\lambda=\left(\int p_j^{1-\sigma}dj\right)^{\frac{1}{1-\sigma}}.$$

The first order condition can then be rearranged as

$$y_j=\left(\frac{p_j}{P}\right)^{-\sigma}\mathbf{y} \tag{14}$$

Finally to see that this is the correct interpretation of P as a price index for the aggregate good $\mathbf{y}$, observe that local non-satiation implies that

$$\int p_j y_j dj = I,$$

or, using (14),

$$\int p_j \mathbf{y} \left(\frac{p_j}{P}\right)^{-\sigma} dj = I.$$

Rearranging, we obtain

$$\begin{aligned} \mathbf{y}\left(\frac{1}{P}\right)^{-\sigma} \int p_j^{1-\sigma} dj &= I \\ \mathbf{y} P^{\sigma} P^{1-\sigma} &= I \\ \mathbf{y} P &= I. \end{aligned}$$

■

Proof of Proposition 2. The first order condition for investment is

$$u'(\mathbf{c}_t) = \beta u'(\mathbf{c}_{t+1})\left[r_{j,t+1} + 1 - \delta_j\right].$$

Since in equilibrium consumption is constant over time the result follows immediately.

■

Proof of Proposition 3. The result follows immediately from the fact that $s_{hj} = 1/N_j$ in a symmetric equilibrium. ■

Proof of Proposition 4. We can write the inverse demand function as

$$p = \left(\frac{zk^{\alpha} l^{1-\alpha} + \widehat{Y}_{-h}}{I} \right)^{\frac{-1}{\sigma}} \tag{15}$$

This implies that static profits are given by

$$\pi\left(\widehat{Y}_{-h}\right) = \max_{k,l} \left\{ \left(zk^{\alpha} l^{1-\alpha}\right)^{1-1/\sigma} \left(\frac{\widehat{Y}_{-h}}{I}\right)^{\frac{-1}{\sigma}} - wl - r_j k - \kappa w \right\}$$

It is clear that profits will decline with $\widehat{Y}_{-h}$ – which will increase with N – for any value of $\sigma > 0$. In the Cournot game, the firm's profit function is increasing and concave in l and k provided $\sigma > 1$, so there is a unique solution. However, it is decreasing in l and k if $\sigma < 1$, so there is no solution to the firm's problem and no equilibrium. ■

Proof of Proposition 5. The proof follows from the fact that V is decreasing in N and decreasing in δ_j. Hence, given δ, the highest N that satisfies the free entry condition $V_h\left(\left(N-1\right)y_h\right) \geq c_e w_t$ must be weakly decreasing in δ_j. V is continuous in parameters, so that there must exist a value of δ_j such that the entry cost is satisfied with equality. Call this δ_N. This implies that for sufficiently small $\varepsilon > 0$ we have that $N\left(\delta_N - \varepsilon\right) = N\left(\delta_N\right)$: on the other hand, for any $\varepsilon > 0$, $N\left(\delta_N + \varepsilon\right) < N\left(\delta_N\right)$. ■

Proof of Proposition 6. The result follows from Proposition 5 and the fact that the markup equals $\frac{1}{1-1/\varepsilon_j} = \frac{\sigma N_j}{\sigma N_j - 1}$. ■

Proof of Proposition 7. We are assuming an equilibrium exists, so $\mathbf{N} \neq \varnothing$. For each $N \in \mathbf{N}$ define

$$\Delta^* (N) = \sup \left\{ \delta_j \in \left[\underline{\delta}, \overline{\delta}\right] : V_h \left((N-1)\, y^* (N) \,| j \right) = c_e w \right\}.$$

The first result follows from the fact that $N(\delta_j)$ is decreasing and lower hemicontinuous. The second result follows from the continuity of decision rules in the wage.

■

Proof of Proposition 8. The result follows from the fact that $N(\delta_j)$ is decreasing and lower hemicontinuous, and the continuity of decision rules in the relevant parameters.

■

D Markup Calculations

We calculate firm-level markups of price over marginal cost following the production approach as presented in De Loecker et al. (2020). This approach is based on the framework of De Loecker and Warzynski (2012) that integrates insights from Hall (1988). Unlike the standard approach in the Industrial Organization literature which derives markups from the first order condition of optimal pricing combined with price-elasticities of demand and assumptions on how firms compete, this approach is not conditioned on the specification of the demand system or assumptions on firm competition.

According to this production approach, markups are backed out from the cost minimization conditions of a variable input of production. At time t, firm i minimizes costs based on a production function that transforms the vector of variable inputs $\mathbf{V}$ and capital stock K_{it} into output Q_{it}. While individual variable inputs vary and might include labor, intermediate inputs, materials... due to the nature of variable input reporting in Compustat, we treat all individual variable inputs as a *bundle*, and thus the vector $\mathbf{V}$ of variable inputs as a scalar V.

Following De Loecker et al. (2020), markup is defined as $\mu = \frac{P}{\lambda}$ where P is the price of the output good and λ is the Lagrange multiplier of the Lagrangian objective function associated with the firm's cost minimization. The Lagrange multiplier is considered a direct measure of marginal cost as it represents the value of the objective function as output constraints are loosened.

From a rearrangement of the first order condition with respect to the variable input

V and plugging in the fraction that expresses λ, the formula to calculate markup can be obtained as follows:

$$\mu_{it} = \theta^v_{it} \frac{P_{it} Q_{it}}{P^V_{it} V_{it}} \tag{16}$$

where θ^v_{it} is the output elasticity of bundle of variable inputs V, P_{it} is the price of the output good, and P^V_{it} is the price of the variable input bundle V. θ^v_{it} measures the sensitivity of output to changes in variable inputs and can be derived from the first order condition of the Lagrangian objective function for cost minimization of the firm:

$$\theta^v_{it} \equiv \frac{\partial Q(.)}{\partial V_{it}} \frac{V_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P^V_{it} V_{it}}{Q_{it}} \tag{17}$$

where $Q(.)$ represents the technology of production or the form of the production function.

We can break down equation 16 that expresses markups into two components: (i) the output elasticity of the variable input bundle θ^v_{it} and (ii) the ratio of revenue from selling the output good $(P_{it} Q_{it})$ to the cost of the variable input bundle $(P^V_{it} V_{it})$. The second component can be calculated from the Compustat database as it records both net sale (revenue) and the cost of goods sold (cost of the variable input bundle). It remains a task to estimate the first component which is θ^v_{it}.

There are two main methods to estimate the output elasticity of the variable input of production. The first method is to estimate θ^v_{it} from a parametric production function. According to this method, the output elasticity of the variable input bundle is the coefficient of the variable input bundle in the production function with this variable input bundle and capital as inputs. The estimation of the production function, at the same time, adopts standard techniques in the literature [7] to address the endogeneity issues which arise from the presence of the determinants of production e.g. productivity shocks that are observable to the firm but not observable to an econometrician. Accordingly, the identification strategy would happen through a two-stage approach where a control function of optimal input (static) or investment (dynamic) demand is inverted to allow us to control for unobserved productivity shocks. De Loecker et al. (2020) find that results obtained using either the static or dynamic processes are very similar to each other.

While following these standard practices, De Loecker et al. (2020) consider both time-varying and sector-specific production function parameters for each of the 22 sectors at the 2 digit NAICS level. Thus, θ_{it}^{v} varies across sectors and across time under their assumptions. Multiplying this time-varying and sector-specific parameter by the ratio of revenue to cost of goods sold, we get measures of markups that varies across firms, allowing for the consideration of firm heterogeneity of markups in our analyses. The output elasticity of variable input of our interest is thus the parameter θ_{st}^{V} for each given industry s in the Cobb-Douglas production function that is estimated at the firm level as follows:

$$q_{it} = \theta_{st}^{V} v_{it} + \theta_{st}^{K} k_{it} + \omega_{it} + \epsilon_{it} \tag{18}$$

[7] Some well-known techniques have been proposed by Olley and Pakes (1996) Levinsohn and Petrin (2003), and Ackerberg et al. (2015)

While this method helps overcome the potential biases in estimating the output elasticity variable, its implementation is operationally complex as it requires the identification of an optimal input decision, the inversion of which allows the econometrician to account for unobserved productivity shocks.

At the same time, the second method to estimate θ_{it}^{v} is to approximate it to the share of expenditures on the variable input bundle in total cost. While this second method can be performed without the need to estimate the production function and thus circumvents the challenging identification issues, it requires time-invariant technological parameters and constant returns to scale in production.

As the main focus of our paper is to explore the role of technological characteristics of production in industry competition, we apply time-varying production function coefficients in order to better capture factor-driven technological changes and consequently the impact of variations in technological characteristics in our analyses. Thus we follow the first method to calculate the output elasticity of variable input that is backed out from the time-varying and sector-specific production function parameters, which is a major contribution of De Loecker et al. (2020). The production function method to calculate output elasticity of variable input bundle from time-varying technological parameters (which gives us the markup measure Mu_2) is used in parallel with our time-invariant measure (Mu_1) as a robustness check for our results. We also calculate another markup measure (Mu_3) with output elasticity measures backed out from an alternative production function (referred to as PF2) that includes overhead costs reported under "Selling, General and Administrative Expenses" (SG&A, denoted as XSGA in Compustat) apart from the baseline production specification 18 (PF1).

While we directly calculate the ratio of revenue to cost of goods sold using Compustat data, we use the output elasticity measures under specifications discussed above from the data published by De Loecker et al. (2020).