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A QUIEN CORRESPONDA

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Por la presente certifico que, el Sr. TRISTANY ARMANGUE con DNI número 23867372L está matriculado como estudiante a tiempo completo del primer curso en los estudios de Doctorado Internacional en Análisis Económico para el curso 2023-2024.

El Sr. Tristany Armangué continuará con sus estudios de Doctorado en Análisis Económico IDEA en el curso 2024-2025 trabajando en su tesis doctoral bajo la supervisión del Dr. Nezih Guner.

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Y para que conste, a los efectos oportunos, expido el presente certificado en Bellaterra, Cerdanyola del Vallés a 14 de junio de dos mil veinticuatro.

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Firm Dynamics, Monopsony, and Aggregate Productivity Differences*

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[PRELIMINARY AND INCOMPLETE]

Abstract

Labor market power lowers efficiency and leads to aggregate output losses. In this paper, we study the cost of labor market power through the lens of a dynamic model of neoclassical monopsony with occupational choice. The model is consistent with evidence of higher life-cycle firm growth and higher productivity investment in more competitive labor markets. The model delivers these facts through three mechanisms, two of which are novel: 1) static labor allocation, 2) selection into entrepreneurship, and 3) dynamic misallocation of resources through lack of investment in R&D. We find that all mechanisms lead to significant output losses, suggesting that the costs of labor market power may be larger than reported by previous research.

Keywords: labor market power, monopsony, firm dynamics, productivity
JEL Classification: E24, J42, L13

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1 Introduction

Labor market power distorts the allocation of workers across employers, leading to efficiency losses and lower output per capita (Berger et al., 2022; Amodio et al., 2022; Armangué-Jubert et al., 2024). In this paper we show how labor market power, in addition to its static misallocation effect, distorts dynamic investment decisions and selection into entrepreneurship. To study these different channels, we build a general equilibrium model of the labor market featuring occupational choice between entrepreneurship and wage employment, dynamic investment decisions by entrepreneurs and taste shocks for employers à la Card et al. (2018), which limit the elasticity of labor supply to wages.

The model can account for many stylized facts found in cross-country data, including larger firm-size growth, higher average firm size, larger share of investment in R&D and higher average firm age, all of which are features of countries characterized by more competitive labor markets.

In the model, labor market power reduces aggregate efficiency through three different channels. The first channel is standard in models of neoclassical monopsony (Card et al., 2018; Dustmann et al., 2022; Armangué-Jubert et al., 2024) and it operates through the *static allocation* of workers: lower competition increases the marginal factor cost only for a subset of firms with sufficiently high productivity, spurring employment reallocation towards less-productive, lower-paying employers. The other two mechanisms are novel. Under imperfect competition in the labor market, *selection into entrepreneurship* is distorted: profits are a function of non-productivity attributes of entrepreneurs which allows low productivity agents to reap high benefits from entrepreneurship. And finally, lack of competition induces *dynamic misallocation* of resources by reducing investment in R&D: monopsony endows firms with excess profits and a lesser need to innovate, hampering firm growth.

We calibrate the model to the Netherlands using microdata from the World Bank Enterprise Surveys and use counterfactual experiments to quantify the importance of each mechanism. We find that all mechanisms lead to significant output losses, suggesting that the costs of labor market power may be larger than reported by previous research. In a counterfactual exercise where we impose the median markdown found in Greece to the baseline calibration for the Netherlands, the model predicts a fall of GDP per capita of 35 percent. In a decomposition exercise, we find that 22 percentage points are attributable to the static labor allocation channel, 5 percentage points are explained by the dynamic misallocation caused by lower investment, and 8 percentage points are explained by changes in selection into entrepreneurship.

This paper builds on the growing literature on labor market power, how it changes across countries, and its effects on the aggregate economy. Armangué-Jubert et al. (2024) document, using a structural estimation of a general equilibrium model of oligopsony, that markdowns are decreasing with income per capita for countries with GDP per capita levels of over $2,000. In a related paper, Amodio et al. (2024) estimate median markdowns across 82 low and middle income countries and find a hump shape relationship with GDP per capita, which in their sample of countries can be explained by differences in self-employment rates. Our paper estimates median markdowns across middle and high income countries following Levinsohn and Petrin (2003) and documents them to be decreasing with GDP per capita, consistent with the cross-country findings of Armangué-Jubert et al. (2024) and Amodio et al. (2024).

Another active area of research studies the costs of labor market power. Berger et al. (2022) use a model of oligopsony to estimate the welfare losses from labor market power in the US, and find them to be 6 percent of lifetime consumption relative to the efficient allocation. Deb et al. (2022) find that one-quarter of the wage stagnation observed in the US over the last four decades can be explained by increased monopsony power. Amodio et al. (2022) study the relationship between self-employment and labor market power in Peru, and find that in the absence of labor market power the share of people in wage employment would increase by 10 percentage points and average earnings would increase by around 30 percent in both the wage employment and the self employment sectors.

The paper is also related to recent work that studies the amplification of costs of monopsony due to dynamic and selection effects. Bachmann et al. (2022) use administrative data from Germany to show that monopsony leads firms to stay inefficiently small, invest less in marketing and be less productive. Finally, Deb (2023) builds a model of occupational choice to study the effects of market structure on entrepreneurship and finds that increased levels of market power can explain the fall of entrepreneurship and the rise of income inequality observed in the US since the 1980s. However, none of those papers studies the welfare costs of labor market power accounting for static labor misallocation, dynamic misallocation through investment, and selection into entrepreneurship.

Finally, this paper is related to the macro-development literature that studies how differences in frictions and distortions can help explain observed cross-country differences in income per capita. (e.g. Guner et al., 2008; Hsieh and Klenow, 2009; Bento and Restuccia, 2017a; Guner and Ruggieri, 2022; Tamkoç and Ventura, 2024). We contribute to this literature by showing that differences in labor market power lead to differences in static labor allocation, selection into entrepreneurship, and firm investment decisions, that can explain a significant fraction of the observed gaps in GDP per capita across countries.

2 Stylized Facts

Our main data source is the World Bank Enterprise Surveys (WBES), conducted by the World Bank. WBES is an establishment-level survey and it is a representative sample of non-agricultural and non-financial private firms with at least 5 full-time permanent employees. It follows a stratified sampling methodology along sectors, establishment size, and location with a common questionnaire for more than 90 countries from 2006 to 2021. It covers information on firm-level sales, number of workers, labor cost, the value of machinery, cost of raw materials, and intermediate goods employed in production, together with a large set of additional plant-level demographic characteristics, e.g., age, sector, and location, among others. We complement this data with other aggregate variables, such as real GDP per worker in 2017 USD from the World Bank's World Development Indicators (WDI).

We restrict our focus to countries that ever had a GDP per capita of above

$25,000 during the years in which the survey was conducted (Tamkoç and Ventura, 2024) and only consider firms with non-missing observations on annual sales and number of workers. As a result, we have 31 countries in our sample, consisting of middle- and high-income countries. The poorest country in the sample is Kazakhstan, with a GDP per capita of $19,615 in 2009, while the richest one is Ireland, with a GDP per capita of $91,791 in 2020. Table A.1 in Appendix A.1 reports the list of countries and years included in the sample.

As is common in the literature, we conduct our analysis at the local labor market level. A local labor market is defined as a location-industry pair, where locations are the first administrative level of the country and industries are ISIC 3.1.

For each country in our sample, we compute the average firm growth, the average firm size, the average firm age, the average share of firms that innovate, and the mean and median markdowns for its representative local labor market. To that end, we first compute those indicators for each local labor market in a country and then take a weighted average over local labor markets.

We use firms' current employment and employment at birth to compute unconditional average firm growth and average firm growth at 40 years of operations[1]. Similarly, we use firms' first year of operations to compute average firm age. To compute the share of firms that innovate, we use the share of firms that report having conducted formal research and development activities[2].

Finally, to compute mean and median markdowns we begin by estimating, at the firm level, the ratio of firms' marginal revenue product of labor and the wage paid (Amodio et al., 2024). To do so, we first assume a Cobb-Douglas revenue production function specification,

$$\ln y_{it} = \alpha + \beta \ln(\ell_{it}) + \gamma \ln(k_{it}) + \delta_w \ln(m_{it}) + \omega_{it} + \epsilon_{it}$$

where y_{it} is firm sales, ℓ_{it} denotes number of employees, k_{it} is capital, m_{it} mate-

[1]The findings are robust to conditioning firm growth on different ages, as shown in Appendix XXX

[2]The question asked by WBES is "During last fiscal year, did this establishment spend on formal research and development activities, either in-house of contracted with other companies, excluding market research surveys?".

rials of firm i and time t. Finally, ω_{it} captures a combination of productivity differences across firms and demand-side factors affecting the output price, while ϵ_{it} is instead an unobserved iid idiosyncratic shock to revenues with mean zero.

We estimate the parameters of the revenue production function separately for each country and year in the sample using a control function approach as in Levinsohn and Petrin (2003).[3] Using the estimates for revenue elasticity of labor, $\hat{\beta}$, we derive the wage markdown as a ratio between the marginal revenue product of labor and the wage paid by firm i at time t,

$$\mu_{it} = \frac{\mathrm{MRPL}_{it}}{w_{it}}$$

where

$$\mathrm{MRPL}_{it} = \frac{\partial y_{it}}{\partial \ell_{it}} = \hat{\beta}\frac{y_{it}}{\ell_{it}}$$

Our set of cross-country estimates of average firm growth, average firm size, average firm age, average share of firms that innovate, and the mean and median markdowns, together with the levels of income per capita of those countries lead us to three stylized facts.

Firm dynamics. Firms in countries with high GDP per capita grow faster in size over their life cycle and are older on average. Figure 1 shows both sets of estimates across countries, together with fitted lines from auxiliary regressions on GDP per capita.

Previous research has documented a positive relationship between average firm size and GDP per capita (Poschke, 2018), we replicate those findings in Appendix XXX. Hsieh and Klenow (2014) document faster firm size growth in the US compared to Mexico and India, which they attribute to lower investment in firm-specific organizational capital due to larger frictions for large firms in Mex-

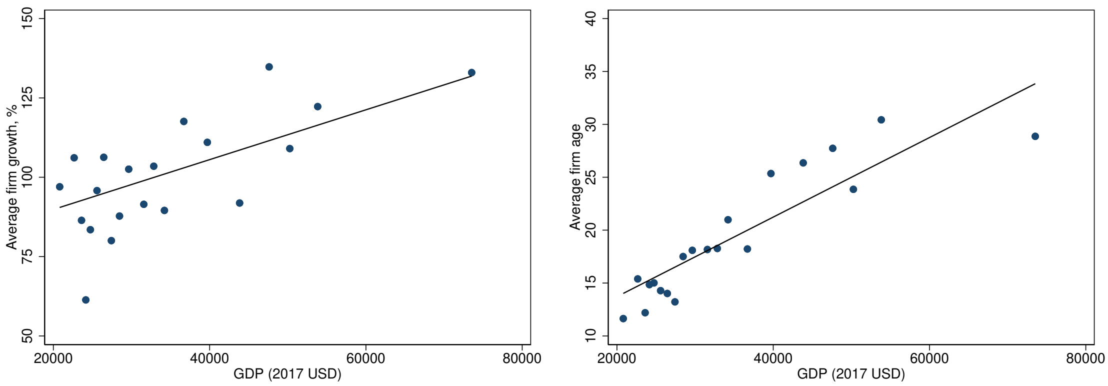
[3]This method relies on three main assumptions: (i) the term ω_{it} evolves according to a first-order Markov process; (ii) the term ω_{it} is the only unobservable in the firm's input demand function; and (iii) the input demand function is invertible in ω_{it}. Under these three assumptions, we can control for unobserved productivity and demand shocks non-parametrically, using materials and capital as proxy variables.

ico and India compared to the US. The evidence of higher rates of firm growth in more developed economies suggests that the cross-country differences in firm sizes are at least partially explained by dynamic firm decisions, such as investment in R&D.

The evidence showing a positive relationship between GDP per capita and average firm age is, to the best of our knowledge, novel and it points to lower firm churn in more developed economies and tougher selection.

Figure 1: Firm dynamics over development

(a) Average firm size growth, unconditional | **(b)** Average firm age

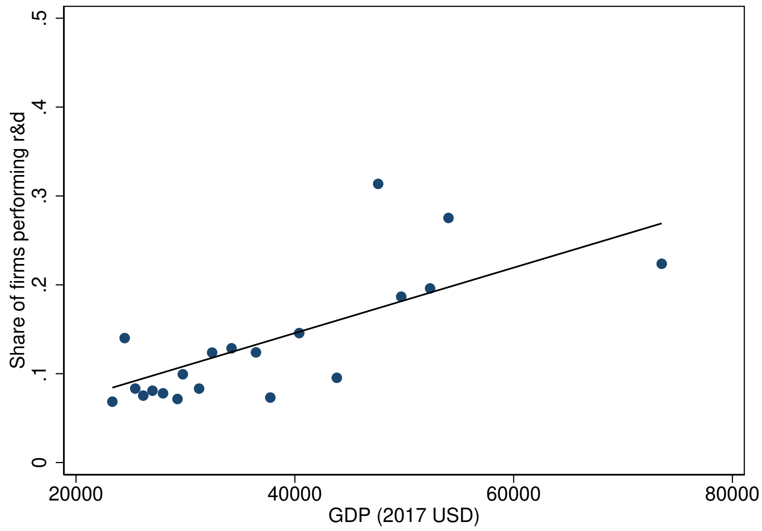


NOTES: Panel A shows a binscatter of the average firm size growth across countries and a fitted line from an auxilliary regression on GDP per capita. Panel B shows a binscatter of the average firm age across countries and a fitted line from an auxilliary regression on GDP per capita.

Innovation. Figure 2 reproduces the second stylized fact: firms in high GDP per capita countries are more likely to perform R&D, and to invest in innovation. This is consistent with recent findings in Farrokhi et al. (2024), who show that distortions in the labor market can explain the inefficiently low adoption of technology in low-income countries.

Figure 2: Firm innovation over development

(a) R&D

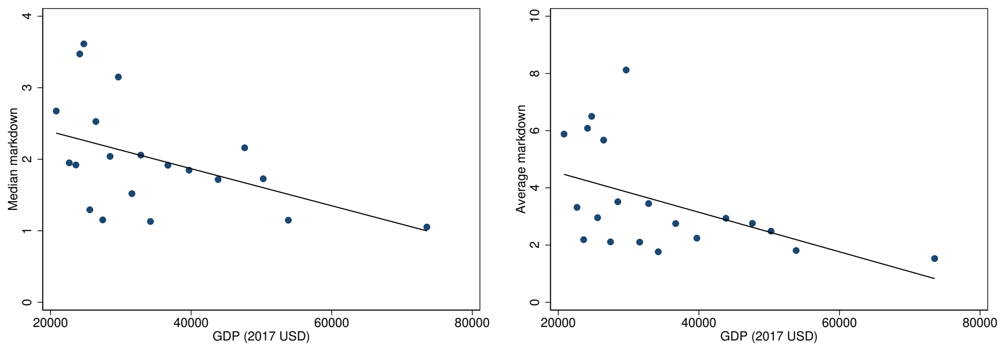


NOTES: The figure shows a binscatter of the share of firms that innovate across countries and a fitted line from an auxilliary regression on GDP per capita.

Labor Market Power. Figure 3 reproduces the third stylized fact: on average, firms in high income countries charge lower markdowns. Amodio et al. (2024) document a hump-shaped relationship between GDP per capita and median markdowns for countries with GDP per capita levels below $25,000. Our estimated markdowns for countries just above this threshold are consistent with their estimates for countries just below the threshold. Similarly, our stylized fact is also consistent with Armangué-Jubert et al. (2024), who show that for countries with GDP per capita over $2,000 markdowns are decreasing with income per capita.

Figure 3: Wage markdown over development

(a) Median markdown **(b)** Average markdown



NOTES: Panel A shows a binscatter of the median markdown across countries and a fitted line from an auxilliary regression on GDP per capita. Panel B shows a binscatter of the mean markdown across countries and a fitted line from an auxilliary regression on GDP per capita.

3 Model

We extend a standard model of neoclassical monopsony, as discussed in Card et al. (2018) and Dustmann et al. (2022), to a dynamic general equilibrium setting with an entrepreneurial choice and endogenous productivity investment.

Time is discrete. The economy is populated by a unitary measure of agents, each characterized by entrepreneurial productivity $z \in \mathcal{Z} = [\underline{z}, ..., z_-, z, z_+, ..., \overline{z}]$ and amenities $a \in \mathcal{A}$. Agents face a stochastic lifecycle, with a probability of exiting the labor market equal to δ_w. Before entering the labor market, agents draw a tuple of characteristics (z, a) from two independent distributions, $\Psi_z(z)$, and $\Psi_a(a)$, and, each period following entry, decide whether to become wage workers or entrepreneurs. Let L and $E = 1 - L$ denote the aggregate measures of workers and entrepreneurs in the economy, respectively. Entrepreneurial productivity of every agent evolves stochastically over the life cycle, following a discrete time Poisson process which moves it one step up or down the productivity ladder with probability p_n and 1-p_n (Shimer, 2005). Entrepreneurs can invest in innovation, which increases the likelihood of moving up the ladder to $p_i > p_n$, resulting in a higher expected future productivity. Finally, labor markets are assumed to be spot markets that clear every period: entrepreneurs post wages to maximize their profits, with knowledge of workers' labor supply function. Workers observe posted wages and amenities and choose which firms to work for. Job differentiation through amenities endows entrepreneurs with wage-setting power.

3.1 The problem of the workers

The instantaneous utility for a worker i employed by entrepreneur (firm) j is:

$$u(z_i, a_i, z_j, a_j) = u_{ij} = \epsilon^L \ln(w_j) + a_j + \nu_{ij},$$

where w_j is the wage paid by entrepreneur j, ϵ^L is the elasticity of labor supply, a_j denotes the amenities provided by firm j and ν_{ij} is an iid preference shock for working for firm j, assumed to follow a Gumbel distribution with location parameter 0 and scale parameter σ_v.[4]

Let $\beta \in (0,1)$ be a discount factor. The value function of wage workers is then given by:

$$\begin{aligned} U(z_i, a_i, z_j, a_j) = \epsilon^L \ln(w_j) + a_j + \beta(1-\delta_w)\big(&p_n \max\{\tilde{U}(z_{i+}, a_i), V(z_{i+}, a_i)\} \\ &+(1-p_n)\max\{\tilde{U}(z_{i-}, a_i), V(z_{i-}, a_i)\}\big) \end{aligned}$$

where V is the value of being an entrepreneur and $\tilde{U}$ is the expected value of continuing as a wage worker, defined below. The max operator implies a policy function for entrepreneurial choice, $\rho^e(z_i, a_i)$, defined as

$$\rho^e(z_i, a_i) = \begin{cases} 1 & \text{if} \quad V(z_i, a_i) > \tilde{U}(z_i, a_i), \\ 0 & \text{otherwise} \end{cases}$$

Entrepreneurial productivity increases exogenously by one step on the ladder with probability p_n, while it decreases with the opposite probability, $1 - p_n$.

[4] An alternative approach to generating wage-setting power is to assume CES preferences for differentiated jobs, as in Berger et al. (2022). At the aggregate level, these two approaches are equivalent. See Anderson et al. (1988) and Verboven (1996).

Since the labor market is a spot market and ν_{ij} is assumed to be Type-I EV, the expected value of continuing to be a wage worker is given by:

$$\begin{aligned}\tilde{U}(z_i, a_i) &= \mathbb{E}\left[\max_k \{U(z_i, a_i, z_k, a_k) + \nu_{ik}\}\right] \\ &= \sigma_\nu \ln\left(E\int_{\mathcal{Z}\times\mathcal{A}} \exp\left(\frac{U(z_i, a_i, z_k, a_k)}{\sigma_\nu}\right)\mu(z_k, a_k)dz_k da_k\right)\end{aligned}$$

where $\mu(z, a)$ is the distribution of entrepreneurs across productivity and amenities. The probability that a worker i chooses to work for a firm j is given by the following continuous logit formulation:[5]

$$p_{ij} = \frac{\exp\left(\frac{U(z_i,a_i,z_j,a_j)}{\sigma_\nu}\right)}{\int_L^1 \exp\left(\frac{U(z_i,a_i,z_k,a_k)}{\sigma_\nu}\right)dk}$$

By a change of variable and expanding the value functions, we can re-write the previous expression as:

$$p_{ij} = \frac{\exp\left(\frac{\epsilon^L \ln(w_j)+a_j+\beta(1-\delta_w)\mathbb{E}_{z_i'}\max\{V(z_i',a_i),\tilde{U}(z_i',a_i)\}}{\sigma_\nu}\right)}{E\int_{\mathcal{Z}\times\mathcal{A}} \exp\left(\frac{\epsilon^L \ln(w_k)+a_k+\beta(1-\delta_w)\mathbb{E}_{z_i'}\max\{V(z_i',a_i),\tilde{U}(z_i',a_i)\}}{\sigma_\nu}\right)\mu(z_k, a_k)dz_k da_k}$$

The overall labor supply to a firm j is then:

$$L_j = L\int_{\mathcal{Z}\times\mathcal{A}} p_{ij}\phi(z_i, a_i)dz_i da_i \tag{1}$$

where $\phi(z_i, a_i)$ is the equilibrium distribution of workers across productivity and amenities. Re-arranging terms, equation (1) can be re-written as to:

$$L_j = L\Theta\exp\left(\frac{\epsilon^L \ln(w_j) + a_j}{\sigma_v}\right)$$

[5]See McFadden (1976) and Ben-Akiva et al. (1985).

where

$$\Theta=\int_{\mathcal{Z}\times\mathcal{A}}\left(\frac{\exp\left(\frac{\beta(1-\delta w)\mathbb{E}_{z_i'}\max\{V(z_i',a_i),\tilde{U}(z_i',a_i)\}}{\sigma_V}\right)}{E\int_{\mathcal{Z}\times\mathcal{A}}\exp\left(\frac{\epsilon^L\ln(w_k)+a_k+\beta(1-\delta w)\mathbb{E}_{z_i'}\max\{V(z_i',a_i),\tilde{U}(z_i',a_i)\}}{\sigma_V}\right)\mu(z_k,a_k)dz_k da_k}\right)\phi(z_i,a_i)dz_i da_i$$

The labor supply solution resembles the one obtained in Card et al. (2018): because the labor market is a spot market, dynamic forces only affect the aggregate shifter Θ.

3.2 The problem of the entrepreneurs

Entrepreneurs with ability z_j produce a homogeneous product using a decreasing return to scale production function,

$$Y_j = z_j \ln(L_j) \tag{2}$$

where L_j is the labor supplied to her firm. To make the model tractable, we abstract from capital accumulation and material inputs which we included in our empirical application in Section 2. This also has the added benefit of allowing us to focus on the three mechanisms we introduce below which operate through the monopsonistic labor-market, without adding other confounding channels. Every period, entrepreneurs post a wage w_j to maximize profits given knowledge of the labor supply function. Since entrepreneurs do not observe the preference shocks of individual workers, they cannot perfectly discriminate and will offer the same wage to all of their workers.

The static problem of the entrepreneur is then given by

$$\max_{w_j} \pi_j(z_j, a_j) = z_j \ln(L_j) - w_j L_j - c_f \tag{3}$$

$$\textit{subject to} \quad L_j = L\Theta \exp\left(\frac{\epsilon^L \ln(w_j) + a_j}{\sigma_v}\right)$$

where c_f is a fixed cost of operation. A solution to this problem is an optimal wage schedule, $W(z, a)$.

Given the solution to the static profit maximization problem, entrepreneurs choose whether to invest in their productivity. Innovation allows entrepreneurs to increase their expected productivity by raising the likelihood of productivity improvement to $p_i > p_n$, and by construction lowering the likelihood of productivity depreciation. To innovate, entrepreneurs incur a per-period fixed cost c_x.

The value to agent i of being an entrepreneur is then given by

$$V(z_i, a_i) = \max\{V^I(z_i, a_i), V^N(z_i, a_i)\} \tag{4}$$

where $V^I(z_i, a_i)$ is the value of investing in productivity, equal to

$$\begin{aligned} V^I(z_i, a_i) = \epsilon^L \ln(\pi(z_i, a_i) - c_z) + a_i + \beta(1 - \delta_w)\big(&p_i \max\{V(z_{i+}, a_i), \tilde{U}(z_{i+}, a_i)\} \\ &+(1 - p_i) \max\{V(z_{i-}, a_i), \tilde{U}(z_{i-}, a_i)\}\big) \end{aligned}$$

while $V^N(z_i, a_i)$ is value of not investing,

$$\begin{aligned} V^N(z_i, a_i) = \epsilon^L \ln(\pi(z_i, a_i)) + a_i + \beta(1 - \delta_w)\big(&p_n \max\{V(z_{i+}, a_i), \tilde{U}(z_{i+}, a_i)\} \\ &+(1 - p_n) \max\{V(z_{i-}, a_i), \tilde{U}(z_{i-}, a_i)\}\big) \end{aligned}$$

The max operator in equation (4) implies a policy function for investment into innovation, $\rho^z(z_i, a_i)$, defined as

$$\rho^z(z, a) = \begin{cases} 1 & \text{if} \quad V^I(z_i, a_i) > V^N(z_i, a_i), \\ 0 & \text{otherwise} \end{cases}$$

3.3 Equilibrium

A stationary recursive equilibrium is a list of value functions $V(z_i, a_i)$, $U(z_i, a_i, z_j, a_j)$ and $\tilde{U}(z_i, a_i)$, an associated entrepreneurship policy function $\rho^e(z_i, a_i)$ and innovation policy function $\rho^z(z_i, a_i)$, a wage schedule $W(z_i, a_i)$, an allocation of labor supply $L(z_i, a_i)$, an aggregate measure of workers L, a distribution of agents over productivity and amenities, $\Omega(z_i, a_i)$, and distributions of wage workers and entrepreneurs over productivity and amenities, $\phi(z_i, a_i)$ and $\mu(z_i, a_i)$, such that:

- The labor supply, $L(z_i, a_i)$ to each firm satisfies equation (1);
- $\rho^e(z_i, a_i)$ and $\rho^z(z_i, a_i)$ solve the entrepreneurial and the innovation choices, and the value functions $V(z_i, a_i)$, $U(z_i, a_i, z_j, a_j)$ and $\tilde{U}(z_i, a_i)$ attain their maxima;
- The aggregate measure of workers is consistent with the entrepreneurial choices:
$$L = \int_{\mathcal{Z}\times\mathcal{A}} (1 - \rho^e(z_i, a_i))\Omega(z_i, a_i) dz_i da_i;$$
- The distribution of agents over productivity and amenities, $\Omega(z_i, a_i)$ is stationary and replicates itself through entry and exit, and the policy functions, as in equations (8), (9) and (10), defined in Appendix B.2.
- The distributions of wage workers and entrepreneurs over productivity and amenities are stationary and defined as
$$\phi(z_i, a_i) = \frac{(1 - \rho^e(z_i, a_i))\Omega(z_i, a_i)}{\int_{\mathcal{Z}\times\mathcal{A}} (1 - \rho^e(z_i, a_i))\Omega(z_i, a_i) dz_i da_i},$$
  and
$$\mu(z_i, a_i) = \frac{\rho^e(z_i, a_i)\Omega(z_i, a_i)}{\int_{\mathcal{Z}\times\mathcal{A}} \rho^e(z_i, a_i)\Omega(z_i, a_i) dz_i da_i},$$
  respectively.

A solution algorithm is presented in Appendix B.3.

3.4 Discussion

In the model, labor market power affects firm dynamics and allocation efficiency through different channels.

To gain some insights, let us assume for clarity that $\sigma_v = 1$.[6] Notice that profit maximization (3) subject to equation (1) yields the following equilibrium employment choice by firm j:

$$\ln(L_j) = \frac{\epsilon^L}{1+\epsilon^L}\ln(z_j) + \frac{1}{1+\epsilon^L}a_j + C$$

where $C = \frac{1}{1+\epsilon^L}\left[\epsilon^L \ln\left(\frac{\epsilon^L}{1+\epsilon^L}\right) + \ln(L) + \ln(\Theta)\right]$ is a market-level constant. Rearranging the equation above, we obtain that the relative employment between firms with a low- and high-productivity, $\underline{z}$ and $\overline{z}$, and same amenities a, equals:

$$\frac{L(\overline{z}, a)}{L(\underline{z}, a)} = \left(\frac{\overline{z}}{\underline{z}}\right)^{\frac{\epsilon^L}{1+\epsilon^L}} \tag{5}$$

Similarly, the relative employment between firms with low- and high-amenities, $\underline{a}$ and $\overline{a}$, and same productivity z, is equal to:

$$\frac{L(z, \overline{a})}{L(z, \underline{a})} = \left(\frac{\overline{a}}{\underline{a}}\right)^{\frac{1}{1+\epsilon^L}} \tag{6}$$

Equations (5) and (6) predict that when the labor supply elasticity rises, relative employment falls at the lower-productivity and higher-amenities firms. This effect is standard in static models of classical monopsony (Card et al., 2018; Armangué-Jubert et al., 2024).[7] With a constant aggregate labor supply L, an equilibrium reduction in relative employment at lower-productivity and higher-amenities firms implies labor reallocation towards high-productivity firms and away from high-amenities firms. We summarize this result in the following proposition

Proposition 1 *Everything else equal, labor reallocates towards high-productivity firms and away from high-amenities firms when the labor supply elasticity, ϵ^L, increases.*

Proof 1 *Immediate from equations (5) and (6).*

[6]This is not a binding assumption in any of the propositions.
[7]See Autor et al. (2023) for a detailed discussion.

In equilibrium, entrepreneurs make profits equal to

$$\pi_j(z_j, a_j) = z_j \left(\frac{\epsilon^L}{1+\epsilon^L} \ln(z_j) + \frac{1}{1+\epsilon^L} a_j + C - \frac{\epsilon^L}{1+\epsilon^L} \right) - c_f \tag{7}$$

where C is as defined above. Notice that profits are increasing and convex in productivity z_j, i.e. $\partial\pi_j(z_j, a_j)/\partial z_j > 0$ and $\partial^2\pi_j(z_j, a_j)/\partial z_j^2 > 0$, Everything else equal, it can be shown that the convexity of profits with respect to productivity is higher when the elasticity of labor supply increases[8]. Higher convexity of profits makes the returns to innovate, i.e., the returns from climbing up the productivity ladder, lower for low-productivity firms and higher for high-productivity firms. We summarize this result in the following proposition.

Proposition 2 *Returns to innovation are relatively higher for high-productivity firms when ϵ^L is higher.*

Proof 2 *See Appendix B.4.*

Finally, notice from equation (7) that profits are increasing in amenities a_j, i.e $\partial\pi_j(z_j, a_j)/\partial a_j > 0$. On the other hand, this relationship weakens when ϵ^L is higher.

Proposition 3 *Profits are increasing in amenities and the slope of the profits-amenities relationship is decreasing in ϵ^L.*

Proof 3 *See Appendix B.4.*

In summary, the model makes 3 predictions regarding economies that go from high to low markdowns: 1) labor reallocates towards more productive firms and away from high-amenity firms, 2) investment shifts towards high-productivity firms and away from low-productivity firms, and 3) low productivity but high amenities agents no longer self-select into entrepreneurship.

[8]See Appendix B.5 for a graphical representation.

4 Calibration

We discipline the model using WBES data for the Netherlands, one of the richest countries in the sample, with an annual GDP per capita of $54,275. We follow Armangué-Jubert et al. (2024) and calibrate the model to replicate the average labor market in the country, as defined by a region-industry pair.

Some parameters are calibrated without solving the model. We chose a model period of a year. We normalize the scale parameter of the Type-I GEV shock, σ_v, to 1. We set the discount factor, β to 0.961, consistent with an annual interest rate of 0.04, and choose δ_w to be 0.025 such that agents spend on average 40 years in the labor market. Finally, we use the estimated wage markdown to back out the labor supply elasticity. Given the monopsonistic labor market structure, the elasticity of labor supply is equal to

$$\epsilon^L = \frac{1}{\mu - 1}$$

where μ is the wage markdown for firms in the local labor market. We set μ equal to the median wage markdown in the Netherlands. In Section 2, we estimated this value to be 1.318. Which implies a labor supply elasticity of 3.145. Table 1 summarizes the value of these parameters and their targets.

Table 1: Parameters Set Without Solving the Model

Parameters	Description	Value	Targets/Source
A	Aggregate productivity shifter	1	normalization
σ_v	Type-I GEV shock scale	1	normalization
β	Discount factor	0.961	annual interest rate=0.04
δ_w	Retirement rate	0.025	40 years in the labor market
ϵ^L	Elasticity of labor supply	3.145	median markdown=1.318

Notes: The table shows the parameters calibrated externally, the values set, and the target or source used.

The remaining parameters are calibrated by minimizing the distance between data moments and simulated moments to reproduce selected features of the baseline economy. Table 2 reports the list of calibrated parameters and their values.

Table 2: Parameters Calibrated

Parameters	Description	Value
c_f	Operating costs	6.46
c_x	Innovation costs	90.9
p_i	Productivity growth of investors	0.73
p_n	Productivity growth of non-investors	0.49
σ_z	Productivity dispersion	2.21
σ_a	Amenities dispersion	1.03

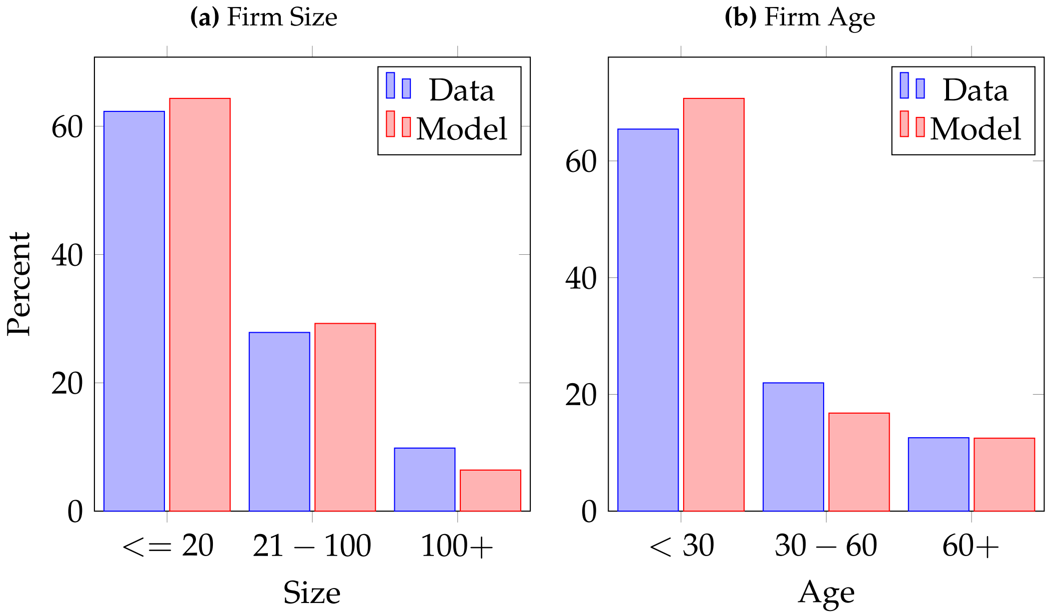
Notes: The table shows the calibrated parameters and their estimated values.

The operating cost, c_f is calibrated to match an average firm size of 34.71 employees while the innovation cost is chosen to match a share of firms investing in R&D of 29.94%. The average employment growth since entry among incumbent firms is 132.1% and it informs the model about the productivity dynamics of investors, p_i whereas the average firm age, 28.93 y.o., will discipline the productivity dynamics of non-investors, p_n through entry and exit into entrepreneurship. Finally, the dispersions in entrepreneurial talents at entry, σ_z, and amenities, σ_a, are disciplined by the standard deviation of (log) firm size (1.321) and (log) wages (0.520), respectively. The fit of the model is quite satisfactory.[9]

The model also replicates the empirical firm size and firm age distributions observed in the Netherlands despite neither being part of the targeted moments. Panel A of Figure 4 reports the percent of firms belonging to different firm size bins, in the data (blue bars) and the model (red bars). About 60% of firms have less than 20 employees, while only around 10% of them employ more than 100 employees, both in the model and the data. Panel B reports the percentage share of different firm age groups in the data and in the model. In both cases, around 65% of firms are under 30 years old, 20% are between 30 and 60, and the remaining 15% are over 60 years old.

[9] Table C1 in Appendix C.1 reports the list of targeted moments and their model counterpart.

Figure 4: Firm Size and Firm Age - Model vs Data

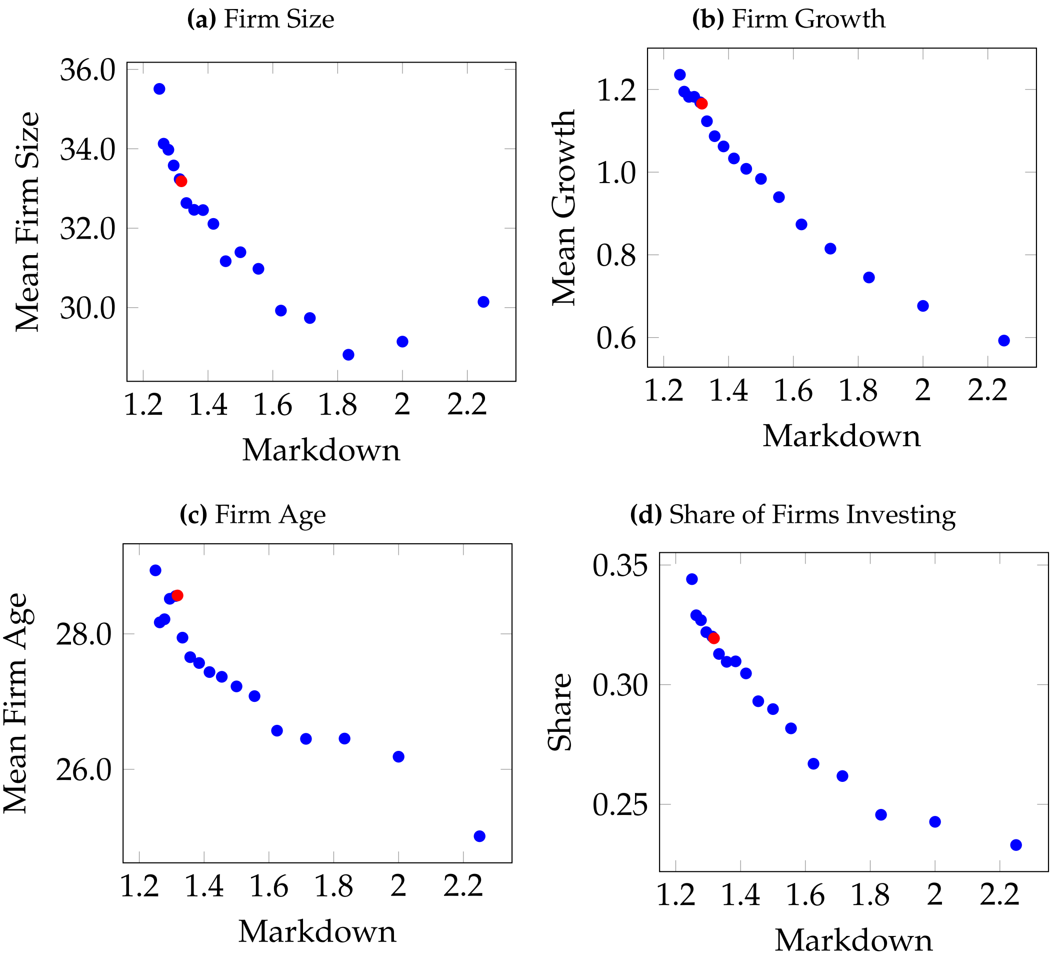


Notes: Blue bars represent the shares of firms over firm size and firm age groups found in the data, red bars show the corresponding shares predicted by the model.

5 Labor market power and firm dynamics

We are ready to discuss how labor market power affects firm dynamics and aggregate productivity. To this end, we construct counterfactual economies that differ from the benchmark only with respect to their labor supply elasticity while leaving all other parameters unchanged. As a result, the counterfactual economies are replicas of the Netherlands, except for differences in ϵ^L. In the benchmark economy, the labor supply elasticity is equal to 3.145, a value chosen to match a median markdown of 1.318. In the counterfactual economies, we let the elasticity vary between 0.8 and 4. These values correspond to wage markdowns ranging from 1.25 to 2.25, the same values estimated for a sample of mid- and high-income countries in Section 2. Figure 5 reports the average firm size (panel A), average life-cycle firm growth (panel B), the share of firms investing in R&D (panel C), and average firm age (panel D), for economies with different degrees of labor market competition. The red dot refers to the benchmark econ-

Figure 5: Firm Dynamics and Labor Market Power

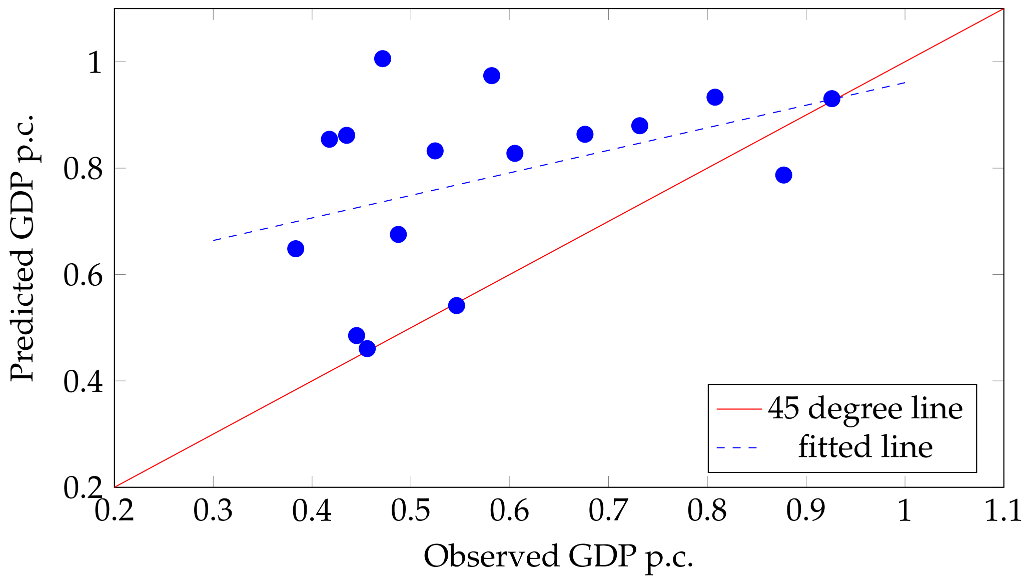


Notes: The red circle refers to the Netherlands. Blue circles refer to counterfactual economies differing in their labor supply elasticity.

omy, the Netherlands. The blue dots refer to counterfactual scenarios.

The average firm size reduces as the labor market becomes less competitive (panel A). Lower labor supply elasticity reduces the average firm size from approximately 42 employees to around 30. Labor market power also affects firm dynamics over the life cycle. Reducing labor market competition leads to a significant reduction in unconditional firm growth (panel B). As wage markdown increases from 1.25 to 2.25, the average firm growth rate shrinks by half, from 125% to about 60%.

Figure 6: Cross-Country Income Differences: Model vs Data



Notes: The blue dots correspond to the binscatter values from Panel A in Figure 3. For each blue dot, we change the value of ϵ^L from our benchmark calibration to the Netherlands to match the corresponding markdown and simulate the model. We then plot the observed GDP relative to the Netherlands in the data agains the predicted GDP relative to the Netherlands in the model.

In the model, firms survive longer and have a higher likelihood of innovation when the labor market is more competitive. Panels C and D in Figure 5 report the average firm age of operating firms and the share of firms investing in innovation across simulated economies, respectively. As we increase the labor supply elasticity, and consequently lower markdowns, the average firm age rises from 25 to 29, and the share of innovators increases from 21 to 34 percent.

Finally, we assess how important is labor market power in generating dispersion in output in our sample of countries. Figure 6 scatter the observed GDP per capita of each country in our sample against the model-based GDP per capita obtained in counterfactual economies that feature the labor supply elasticity in line with our estimates of wage markdown reported in Section 2. As before, all other parameters are kept fixed at their benchmark values. Both observed and simulated values are reported as a fraction of the GDP per capita in the Netherlands.

A few comments are in order. First, there is a positive correlation between simulated and observed GDP per capita across countries. This is because a lower labor supply elasticity generates a high wage markdown, which slows down firm dynamics, reduces efficiency, and lowers GDP per capita. On the other hand, the model generates less variation in output than is observed in the data: the great majority of simulated economies are above the 45-degree line. To quantify the contribution of labor market power, we compute the slope of the relation between model-based and observed GDP per capita. We find the model can account for 42% of the observed variation in GDP per capita across countries. This value is similar to the estimates of GDP losses caused by size-dependent distortions (Restuccia and Rogerson, 2008; Bento and Restuccia, 2017b; Tamkoç and Ventura, 2024), and is larger than gains from reducing firms' labor market power obtained using static models of imperfect competition (Berger et al., 2022; Amodio et al., 2022; Armangué-Jubert et al., 2024).

5.1 Mechanisms

Why does firm dynamics slow down when labor markets are less competitive? In this section, we shed light on the model mechanisms behind the outcomes presented in the previous section. To keep the discussion compact, we compare the benchmark economy (Netherlands) with a single counterfactual economy, featuring the same degree of labor market power observed in Greece. This choice is motivated by two reasons, i.e. i) Greece has one of the lowest GDP per capita in the sample, approximately one-half of that of the Netherlands (29,000 USD vs. 54,000 USD); and ii) the degree of labor market competition is much weaker in Greece than the Netherlands: the estimated wage markdown is equal to 2.62 (vs 1.30), corresponding to an elasticity of labor supply of 0.616 (vs 1.318).

Table 3 reports various outcomes in the benchmarks (column 1) and model-based counterfactuals based on Greece's labor supply elasticity (column 2), and compares the latter to their empirical counterparts (column 3). Compared to the Netherlands, the average firm size is lower in Greece (18 employees vs. 33). Firms grow less over the life cycle (68% vs 117%), survive less (the average age is 19 years vs 29), and are less likely to invest in productivity innovation (32% vs. 11%). Differences in labor market competition can explain 15 percent of the differences in mean firm size between the Netherlands and Greece, account for the differences in average firm growth, and explain 35 and 45 percent of the differences in average firm age and share of firms investing in R&D.

Table 3

	Netherlands Benchmark (1)	Greece Counterfactual (2)	Greece Data (3)	Explained (4)
Share entrepreneurs invest	0.32	0.22	0.11	45.4%
Mean firm size	33.18	30.90	17.87	14.88%
Mean firm age	28.57	25.16	18.90	35.18%
Mean employment growth	1.17	0.50	0.68	138.13%
GDPpc	1.00	0.65	0.54	74.53%

Notes: Column (1) shows selected moments simulated in the baseline calibration to the Netherlands. Column (2) shows the value of the selected moments in the counterfactual where we set ϵ^L to match the median markdown observed in Greece while leaving other parameters unchanged. Column (3) shows the value of the selected moments observed in the data for Greece. Column (4) shows the percentage of the difference between the Netherlands and Greece is explained by differences in markdowns in our model.

To decompose these effects into the three different channels - static allocation of labor, selection into entrepreneurship, and investment in R&D - we run two alternative counterfactuals. In the first alternative counterfactual, we once again use the calibration of the Netherlands as our baseline and change only ϵ^L to match the median markdown of Greece, but impose the entry policy function from the baseline. That is, we solve the model for the counterfactual but keep selection into entrepreneurship fixed. In the second alternative scenario, we do the same exercise and further impose the investment policy function from the baseline. That is, we solve the model for the counterfactual ϵ^L but keep selection into entrepreneurship and investment decisions fixed.

Table 4

	Baseline (1)	Greece (Fixed Entry and Investment) (2)	Greece (Fixed Entry) (3)	Greece (4)
Log GDPpc	1.00	0.78	0.73	0.65
Mean employment growth	1.17	0.59	0.56	0.50
Mean firm age	28.57	28.57	26.08	25.16
Share entrepreneurs invest	0.32	0.31	0.30	0.22

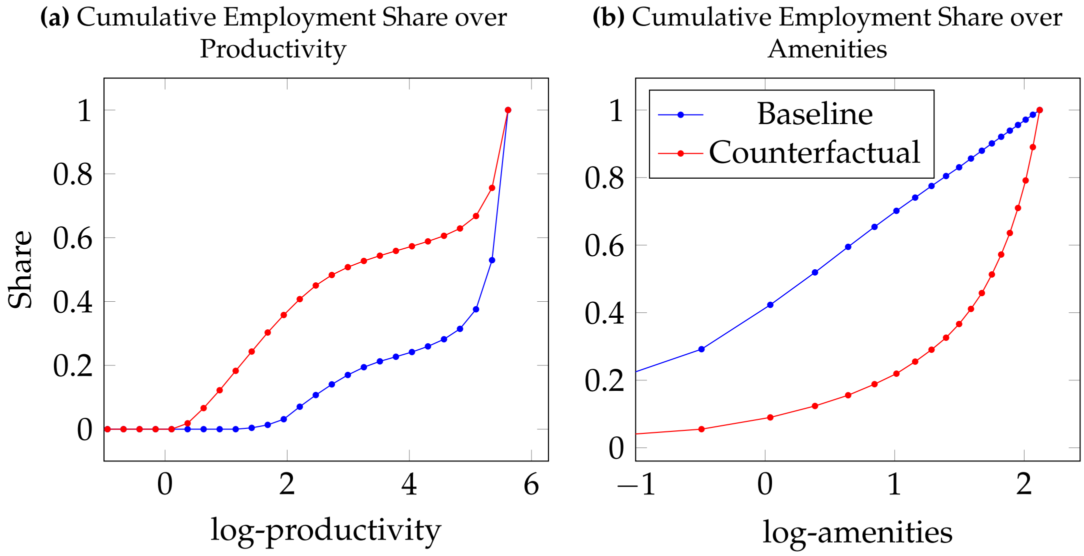
Notes: Column (1) shows selected moments simulated in the baseline calibration to the Netherlands. Column (2) shows the value of the selected moments in the counterfactual where we set ϵ^L to match the median markdown observed in Greece and keep the entry and investment policy functions equal to those in the baseline. Column (3) shows the values of the moments in the counterfactual where we keep only the entry policy fixed at the baseline level. Column (4) shows the values of the simulated moments in the standard counterfactual for Greece.

The second alternative counterfactual, where we keep the entrepreneurship and investment policy functions fixed, captures the effects of monopsony that the model attributes to static labor allocation. The second column of Table 4 shows that this channel accounts for 63 percent of the predicted fall in GDP per capita. Similarly, the difference between the second and third columns of Table 4 shows the effect attributable to changes in investment decisions, which we find to account for 14 percent of the predicted fall in GDP per capita. Finally, the difference between the third and fourth columns shows that selection into entrepreneurship accounts for 23 percent of the observed drop in GDP per capita in our counterfactual.

5.2 Static Allocation of Labor

The first key model prediction, summarized in Proposition 1, is that under higher levels of competition labor is allocated to higher productivity firms and away from unproductive but high-amenity firms. As the relative importance of amenities wanes, and holding all else equal, workers become more responsive to wage differences and competitive forces push firms' posted wages higher and towards the marginal revenue product of labor. As a result, higher degrees of competition reallocate labor away from firms with high amenities but relatively lower productivity and towards firms with higher levels of productivity.

Figure 7: Allocation of Labor and Labor Market Power



Notes: The blue lines show the CDF of employment in the Baseline over log-productivity (Panel A) and over log-amenities (Panel B). The red lines show the corresponding values for the counterfactual with the higher markdowns calibrated to Greece.

Figure 7 shows the cumulative share of employment by firms over levels of firm productivity (Panel A, averaged over amenities) and over levels of firm amenities (Panel B, averaged over productivity). Panel A shows that in the benchmark, calibrated to the Netherlands, the distribution of labor is largely concentrated in the most productive firms in the economy, whereas in the counterfactual, where the elasticity of the labor supply is set to match the much higher markdowns observed in Greece, the distribution of labor over firm productivity is shifted to the left. That is, firms with levels of productivity that under high competition would not be able to grow to certain sizes can do so when they have labor market power.

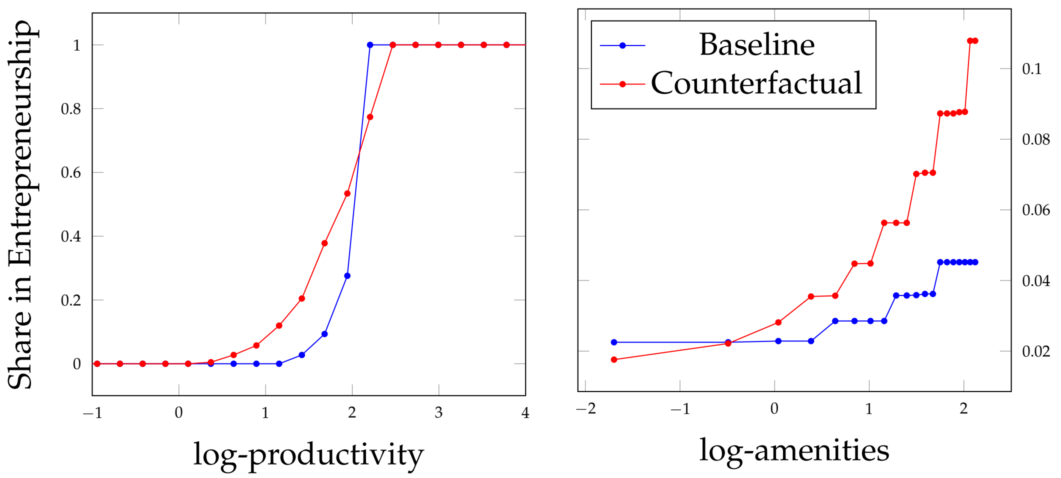
Similarly, Panel B shows that in the counterfactual, with higher levels of labor market power, the distribution of employment over amenities is to the right of the distribution under the baseline. When the relative role of amenities is higher, under low competition, firms with high levels of amenities can grow beyond what they would under high competition. These two findings are consistent with Proposition 1 and demonstrate how the static allocation of labor channel leads to aggregate productivity losses under labor market power.

5.3 Selection into Entrepreneurship

The second channel that we study is selection into entrepreneurship. In the model, agents can choose whether to become entrepreneurs or wage workers, and they internalize the labor supply and labor demand curves in the market when making this decision. When ϵ^L is low, and the relative importance of amenities is high, agents with low entrepreneurial productivity but high amenities anticipate being able to pay low wages, attract workers, and make net profits beyond what they could make as wage workers. This is summarized in Proposition 3.

Figure 8: Selection into Entrepreneurship

(a) Share of Entrepreneurs over Productivity Levels **(b)** Share of Entrepreneurs over Amenities Levels



Notes: Panel A shows the share of agents by productivity level that become entrepreneurs in the baseline calibration to the Netherlands (blue) and counterfactual with ϵ^L set to match Greece's markdowns (red). Panel B shows the share of agents by level of amenities that become entrepreneurs in the baseline (blue) and counterfactual (red).

Figure 8 shows how the share of agents over productivity (Panel C) and amenities (Panel D) that choose to become entrepreneurs changes from the baseline to the counterfactual.[10]

The figure highlights how under the counterfactual, where markdowns are higher and the relative importance of amenities is bigger, the selection into entrepreneurship changes. Specifically, Panel A shows that some agents with high levels of productivity who chose to become entrepreneurs in the baseline do not choose entrepreneurship in the counterfactual and, conversely, some agents with relatively low levels of productivity who did not choose to become entrepreneurs in the baseline choose to do so in the counterfactual. Similarly, Panel B shows that some agents with low levels of amenities that become entrepreneurs in the baseline do not do the same in the counterfactual and that many agents with high levels of amenities that do not choose entrepreneurship in the baseline do choose to start firms in the counterfactual.

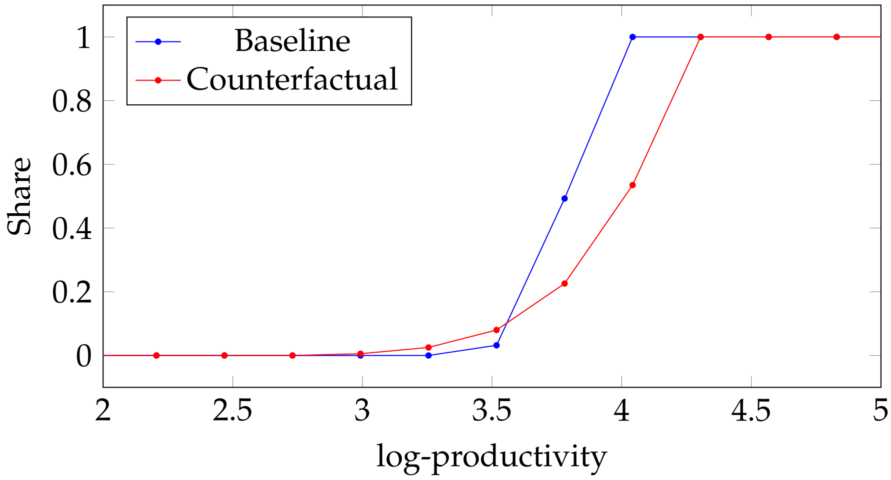
5.4 Investment in R&D

The third channel that is present in the model is investment into productivity. In Proposition 2, we summarized how the relative returns to innovation between high- and low-productivity firms change with labor market power. When ϵ^L is higher, and markdowns are lower, the relative returns to innovation for higher productivity firms are higher. In other words, under more competitive labor markets, the convexity of the profits-productivity curve is greater.

Figure 9 shows how the share of entrepreneurs that conduct R&D by productivity level changes from the baseline to the counterfactual. In the counterfactual, under high markdowns, a significant number of high productivity firms that were investing in the baseline no longer do so. The opposite is also true: some lower productivity firms that do not invest in the baseline do so in the counterfactual, although in our calibration this effect is smaller.

[10]See Appendix XXX for figures showing the change in the policy function for entrepreneurship.

Figure 9: Share of Entrepreneurs that Invest over Productivity Levels



Notes: The blue line shows the share of entrepreneurs that invest in R&D by productivity level in the baseline calibration to the Netherlands. The red line shows the same in the counterfactual where we set ϵ^L to match Greece's observed median markdown.

6 Conclusion

This paper studies how labor market power explains differences in firm dynamics and aggregate efficiency across countries. By calibrating a general equilibrium model of the labor market with occupational choice, dynamic firm investment decisions, and taste shocks for employers, to the Netherlands, we find that countries like Greece, with much higher observed markdowns, could see increases in their income per capita of up to 35 percent if they had levels of labor market competition comparable to those found in the Netherlands.

In a decomposition exercise, we find that approximately 60 percent of the losses to income per capita attributable to labor market power are explained by static allocation of labor effects. Another 15 percent are explained by the distortion to innovation. The remaining 25 percent are explained by the effects on selection into entrepreneurship. These findings bridge the gap between the literature on the effects of labor market power and the studies about the role of frictions and distortions on cross-country income differences, and show that losses from labor market power may be greater than those estimated by previous studies that focus solely on static labor allocation effects.

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A Data Appendix

A.1 Summary of the sample

Table A1: Summary statistics for the harmonized WBES sample merged with GDP per capita in 2017 USD.

Country	Survey Waves	Total Num. Observations
Austria	2021	600
Bahamas, The	2010	150
Belgium	2020	614
Croatia	2007 2013 2019 2023	1871
Cyprus	2019	240
Denmark	2020	995
Estonia	2009 2013 2019 2023	1257
Finland	2020	759
France	2021	1566
Germany	2021	1694
Greece	2018 2023	1198
Hungary	2009 2013 2019 2023	2237
Ireland	2020	606
Israel	2013	483
Italy	2019	760
Kazakhstan	2009 2013 2019	2590
Latvia	2009 2013 2019	966
Lithuania	2009 2013 2019	904
Luxembourg	2020	170
Malaysia	2015 2019	2221
Malta	2019	242

Continued on next page

Table A1: Summary statistics for the harmonized WBES sample merged with GDP per capita in 2017 USD.

Country	Survey Waves	Total Num. Observations
Netherlands	2020	808
Poland	2009 2013 2019	2366
Portugal	2019 2023	2069
Romania	2009 2013 2019 2023	2842
Russian Federation	2009 2012 2019	6547
Saudi Arabia	2022	1573
Slovak Republic	2009 2013 2019	972
Slovenia	2009 2013 2019	955
Spain	2021	1051
Sweden	2014 2020	1191

B Model Appendix

B.1 A simplified 2-period model

Consider a simplified version of the model presented in Section XXX. Agents live for two periods only and do not discount future utilities. At the beginning of the first period, they draw a pair of productivity z_j and amenities a_j from two disjoint distributions and decide whether to become wage workers or entrepreneurs. For simplicity, we assume they remain so for both periods. If they choose to become wage workers, each period they maximize their utility by choosing the firm to which they supply labor. If they choose to become entrepreneurs, they post wages to maximize their profits with knowledge of the labor supply function, and then decide whether to invest in innovation or not.

The per-period problem of the wage workers i reads as follows:

$$\max_k \quad \epsilon^L \ln(w_k) + a_k + \nu_{ik},$$

where w_k and a_k are wage posted and amenities provided by entrepreneur k, respectively, while ν_{ik} is an iid preference shock for working for firm k, assumed to follow a Gumbel distribution with location parameter 0 and scale parameter σ_v.

The probability that a worker i chooses to work for a firm j in a given period is given by a standard logit formulation

$$p_{ij} = \lambda \exp\left(\epsilon^L \ln(w_j) + a_j\right)$$

where $\lambda = \frac{1}{\exp(\sigma_v)\int_L^1 \exp\left(\frac{\epsilon^L \ln(w_k)+a_k}{\sigma_v}\right)dk}$ is an aggregate shifter. The overall per-period labor supply to a firm j is then equal to:

$$L_j = L\int_{\mathcal{Z}\times\mathcal{Z}} p_{ij}\phi(z_i, a_i)dz_i da_i = L\lambda \exp\left(\epsilon^L \ln(w_j) + a_j\right).$$

and the expected value of being a wage worker is given by:

$$\begin{aligned} \tilde{U}(z_i, a_i) &= 2 \times \mathbb{E}\left[\max_k \left\{\epsilon^L \ln(w_k) + a_k + \nu_{ik}\right\}\right] \\ &= 2 \times \sigma_\nu \ln\left(E\int_{\mathcal{Z}\times\mathcal{A}} \exp\left(\frac{\epsilon^L \ln(w_k) + a_k}{\sigma_\nu}\right)\mu(z_k, a_k)dz_k da_k\right) \end{aligned}$$

The static problem of an entrepreneur j is instead given by

$$\begin{aligned} &\max_{w_j} \pi_j(z_j, a_j) = z_j \ln(L_j) - w_j L_j - c_f \\ &\textit{subject to} \quad L_j = L\lambda \exp\left(\epsilon^L \ln(w_j) + a_j\right) \end{aligned}$$

where c_f is a fixed operation cost.

Given the solution to the profit maximization problem, at the end of the first period, entrepreneurs choose whether to invest in their productivity. The value to agent i of being an entrepreneur is then given by

$$V(z_i, a_i) = \max\{V^I(z_i, a_i), V^N(z_i, a_i)\}$$

where $V^I(z_i, a_i)$ is the value of investing in productivity, equal to

$$\begin{aligned} V^I(z_i, a_i) =& \epsilon^L \ln(\pi(z_i, a_i) - c_z) + a_i + \\ & \Big(p_i[\epsilon^L \ln(\pi(z_{i+}, a_i))] + (1 - p_i)[\epsilon^L \ln(\pi(z_{i-}, a_i))] + a_i\Big) \end{aligned}$$

where c_z is the innovation cost, while $V^N(z_i, a_i)$ is value of not investing,

$$\begin{aligned} V^N(z_i, a_i) =& \epsilon^L \ln(\pi(z_i, a_i)) + a_i + \\ & \Big(p_n[\epsilon^L \ln(\pi(z_{i+}, a_i))] + (1 - p_n)[\epsilon^L \ln(\pi(z_{i-}, a_i))] + a_i\Big) \end{aligned}$$

Finally, agents choose to become either wage workers or entrepreneurs and solve the following problem:

$$W(z_i, a_i) = \max\{\tilde{U}(z_i, a_i), V(z_i, a_i)\}$$

To characterize the solution to the model, notice that the profit maximization problem yields the following equilibrium per-period employment choice by firm j:

$$\ln(L_j) = \frac{\epsilon^L}{1 + \epsilon^L} \ln(z_j) + \frac{1}{1 + \epsilon^L} a_j + C$$

where $C = \frac{1}{1+\epsilon^L} \left[\epsilon^L \ln\left(\frac{\epsilon^L}{1+\epsilon^L}\right) + \ln(L) + \ln(\lambda)\right]$ is a market-level constant. Rearranging the equation above, we obtain that the relative employment between firms with a low- and high-productivity, $\underline{z}$ and $\overline{z}$, and same amenities a, equals:

$$\frac{L(\overline{z}, a)}{L(\underline{z}, a)} = \left(\frac{\overline{z}}{\underline{z}}\right)^{\frac{\epsilon^L}{1+\epsilon^L}}$$

Similarly, the relative employment between firms with low- and high-amenities,

$\underline{a}$ and $\overline{a}$, and same productivity z, is equal to:

$$\frac{L(z,\overline{a})}{L(z,\underline{a})} = \left(\frac{\overline{a}}{\underline{a}}\right)^{\frac{1}{1+\epsilon^L}}$$

It is easy to see that when the labor supply elasticity rises, relative employment falls at the lower-productivity and higher-amenities firms. With a constant aggregate labor supply L, an equilibrium reduction in relative employment at low-productivity and high-amenities firms implies labor reallocation towards high-productivity firms and away from high-amenities firms.

Given labor allocations, entrepreneurs make per-period profits equal to

$$\pi_j(z_j, a_j) = z_j \left(\frac{\epsilon^L}{1+\epsilon^L} \ln(z_j) + \frac{1}{1+\epsilon^L} a_j + C - \frac{\epsilon^L}{1+\epsilon^L} \right)$$

where C is as defined above. Entrepreneurs will decide to invest in innovation if $V^I(z_i, a_i) \geq V^N(z_i, a_i)$. This condition simplifies to:

$$(p_i - p_n)[\ln(\pi_i(z_{i+}, a_i)) - \ln(\pi_i(z_{i-}, a_i))] \geq -\ln\left(1 - \frac{c_z}{\pi(z_i, a_i)}\right)$$

Labor market power affects the likelihood of investing by altering relative returns and costs of innovation. Taking the exponential and re-arranging:

$$\exp(p_i - p_n)\frac{\pi_j(z_{j+}, a_j)}{\pi_j(z_{j-}, a_j)} \geq \frac{\pi_j(z_j, a_j)}{(\pi_j(z_j, a_j) - c_z)}$$

B.2 Equilibrium distribution

$$\begin{aligned}
\Omega(z_i, a)' = {} & (1-\delta_w)p_n[(1-\rho^z(z_{i-}, a))\rho^e(z_{i-}, a) + (1-\rho^e(z_{i-}, a))]\Omega(z_{i-}, a) \\
& + (1-\delta_w)p_i\rho^z(z_{i-}, a)\rho^e(z_{i-}, a)\Omega(z_{i-}, a) \\
& + (1-\delta_w)(1-p_n)[(1-\rho^z(z_{i+}, a))\rho^e(z_{i+}, a) + (1-\rho^e(z_{i+}, a))]\Omega(z_{i+}, a) \\
& + (1-\delta_w)(1-p_i)\rho^z(z_{i+}, a)\rho^e(z_{i+}, a)\Omega(z_{i+}, a) \\
& + \delta_w\Psi(z_i, a)
\end{aligned} \tag{8}$$

$$\begin{aligned}\Omega(\overline{z},a)' = {} & (1-\delta_w)p_n[(1-\rho^z(\overline{z}_-,a))\rho^e(\overline{z}_-,a)+(1-\rho^e(\overline{z}_-,a))]\Omega(\overline{z}_-,a)\\ & +(1-\delta_w)p_i\rho^z(\overline{z}_-,a)\rho^e(\overline{z}_-,a)\Omega(\overline{z}_-,a)\\ & +(1-\delta_w)p_n[(1-\rho^z(\overline{z},a))\rho^e(\overline{z},a)+(1-\rho^e(\overline{z},a))]\Omega(\overline{z},a)\\ & +(1-\delta_w)p_i\rho^z(\overline{z},a)\rho^e(\overline{z},a)\Omega(\overline{z},a)\\ & +\delta_w\Psi(\overline{z},a)\end{aligned} \tag{9}$$

$$\begin{aligned}\Omega(\underline{z},a)' = {} & (1-\delta_w)(1-p_n)[(1-\rho^z(\underline{z},a))\rho^e(\underline{z},a)+(1-\rho^e(\underline{z},a))]\Omega(\underline{z},a)\\ & +(1-\delta_w)(1-p_i)\rho^z(\underline{z},a)\rho^e(\underline{z},a)\Omega(\underline{z},a)\\ & +(1-\delta_w)(1-p_n)[(1-\rho^z(\underline{z}_+,a))\rho^e(\underline{z}_+,a)+(1-\rho^e(\underline{z}_+,a))]\Omega(\underline{z}_+,a)\\ & +(1-\delta_w)(1-p_i)\rho^z(\underline{z}_+,a)\rho^e(\underline{z}_+,a)\Omega(\underline{z}_+,a)\\ & +\delta_w\Psi(\underline{z},a)\end{aligned} \tag{10}$$

B.3 Numerical algorithm

The algorithm to solve for equilibrium goes as follows:

1. Guess a stationary distribution of agents over productivity and amenities $\Omega(z,a)^1$.
2. Given the current distribution $\Omega(z,a)^i$:
   (a) Guess the entrepreneurship policy function $\rho^{e,j}(z,a)$.
   (b) Using $\Omega(z,a)^i$ and $\rho^{e,j}(z,a)$, compute the distributions of workers and entrepreneurs over z and a: $\phi(z,a)$ and $\mu(z,a)$, and the measures of workers, L, and entrepreneurs, E.
   (c) Given $\phi(z,a)$, $\mu(z,a)$, L and E, solve the fixed point of the value functions to obtain U, $\tilde{U}$, V, W and Π.
   (d) Using V, and $\tilde{U}$, update $\rho^{e,j+1}(z,a)$.
   (e) Check for convergence of the entrepreneurship policy function, if not equal, return to step (2.b) with the new one.

3. Use Equations (8) and (9) and (10) to get $\Omega(z,a)^{i+1}$, if not sufficiently close to $\Omega(z,a)^i$ return to step 2.

B.4 Proofs from discussion

Recall that in equilibrium, firm-level profits are given by

$$\pi_j(z_j, a_j) = z_j \ln(L_j) - w_j L_j - c_f,$$

where

$$L_j = L\Theta \exp\left(\frac{\epsilon}{1+\epsilon^L}\left(\ln(z_j) - a_j + \ln\left(\frac{\epsilon^L}{1+\epsilon^L}\right) - \ln(L) - \ln(\Theta)\right) + a_j\right)$$
$$w_j = \exp\left(\frac{1}{1+\epsilon^L}\left(\ln(z_j) - a_j + \ln\left(\frac{\epsilon^L}{1+\epsilon^L}\right) - \ln(L) - \ln(\Theta)\right)\right)$$

Proposition 2 *Returns to innovation are relatively higher for high-productivity firms when ϵ^L is higher.*

Proof 2 *Returns to innovation are increasing in productivity,*

$$\begin{aligned}\frac{\partial \pi_j}{\partial z_j} &= \ln(L_j) + z_j \frac{\partial \ln(L_j)}{\partial z_j} - \frac{\partial w_j L_j}{\partial z_j} \\ &= \ln(L_j) + z_j \frac{\epsilon^L}{1+\epsilon^L}\frac{1}{z_j} - \frac{\epsilon^L}{1+\epsilon^L} \\ &= \ln(L_j) > 0\end{aligned}$$

where the inequality holds strictly due to the Inada condition on the utility function. Returns to innovation are convex in z_j:

$$\begin{aligned}\frac{\partial^2 \pi_j}{\partial z_j^2} &= \frac{\partial}{\partial z_j}\left(\ln(L_j)\right) \\ &= \frac{\epsilon^L}{(1+\epsilon^L)z_j} > 0\end{aligned}$$

The convexity of the profits-productivity relationship is increasing in ϵ^L:

$$\frac{\partial}{\partial \epsilon^L}\left(\frac{\partial^2 \pi_j}{\partial z_j^2}\right) = \frac{\partial}{\partial \epsilon^L}\left(\frac{\epsilon^L}{(1+\epsilon^L)z_j}\right)$$
$$= \frac{1}{z_j(1+\epsilon^L)^2} > 0$$

Proposition 3 *Profits are increasing in amenities and the slope of the profits-amenities relationship is decreasing in ϵ^L.*

Proof 3 *Profits are increasing in amenities:*

$$\frac{\partial \pi(z_j, a_j)}{\partial a_j} = z_j \frac{\partial \ln(L_j)}{\partial a_j} - \frac{\partial w_j L_j}{\partial a_j}$$

where $w_j L_j = \frac{\epsilon^L z_j}{1+\epsilon^L}$. So:

$$\frac{\partial \pi(z_j, a_j)}{\partial a_j} = \frac{z_j}{1+\epsilon^L} > 0$$

The slope of the profits-amenities relationship is decreasing in ϵ^L:

$$\frac{\partial}{\partial \epsilon^L}\left(\frac{\partial \pi_j}{\partial a_j}\right) = -\frac{z_j}{(1+\epsilon^L)^2} < 0$$

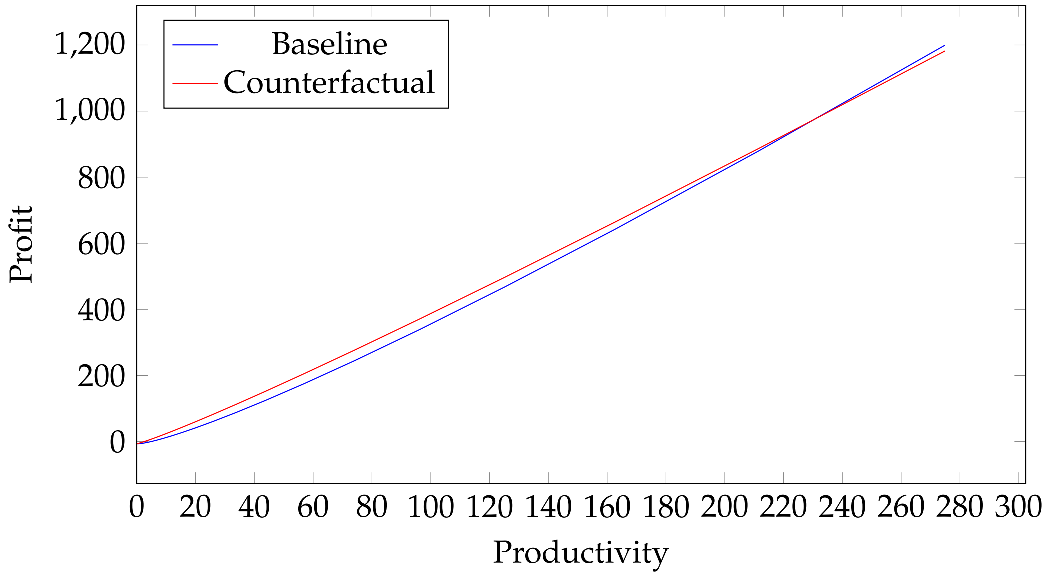
B.5 Graphs for discussion

Recall that the second proposition could be summarized by:

$$\frac{\partial \pi_j(z_j, a_j)}{\partial z_j} > 0$$
$$\frac{\partial}{\partial \epsilon^L}\left(\frac{\partial \pi_j(z_j, a_j)}{\partial z_j}\right) > 0$$

In our baseline and counterfactual estimation, this is evident as shown in the following Figure:

Figure B1: Profits and Productivity



Notes: The diagram shows the relationship between profit and productivity under the baseline and counterfactual, for an arbitrary level of amenities.

C Calibration Appendix

C.1 Model Fit

Table C1 reports the list of targeted moments and their moment counterparts.

Table C1: Model fit

Targets	Data	Model
Average firm size	34.71	33.06
Log firm size dispersion	0.994	1.045
Average employment growth rate	1.321	1.155
Average firm age	28.93	28.25
Log wage dispersion	0.520	0.560
Firms investing in R&D, %	0.299	0.320