Firm Dynamics, Monopsony, and Aggregate Productivity Differences*

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Abstract

This paper studies how labor market power affects firm dynamics and aggregate productivity. We build a dynamic model of neoclassical monopsony with occupational choice, firm growth, and investment in R&D. Labor market power lowers efficiency and leads to aggregate output losses by distorting the allocation of labor, entrepreneurship, and innovation decisions. The model is consistent with cross-country evidence of higher life-cycle firm growth and higher productivity investment in more competitive labor markets and can explain up to 42% of differences in income per capita across countries. We find that about one-third of the losses are attributable to a distorted selection of entrepreneurs and a lack of innovation, suggesting that efficiency losses may be greater than those estimated by previous studies.

Keywords: monopsony, firm dynamics, innovation, productivity
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1 Introduction

Firms are larger and grow faster over the life cycle in high-income countries. A common explanation is that better-functioning markets can improve allocative efficiency, favoring the adoption of better technology (Hsieh and Klenow, 2014). Labor markets are pivotal in the efficient allocation of resources across firms. On the other hand, imperfect competition among employers seems to be a common feature of local labor markets around the world (Amodio et al., 2024). Labor market power is a source of inefficiency that can lower returns to investment in productivity, slow down business dynamism, and explain differences in income across countries.

In this paper, we study how important labor market power is for understanding differences in firm dynamics and aggregate productivity across countries. To this end, we build a general equilibrium model of the labor market featuring an occupational choice between entrepreneurship and wage employment, dynamic investment decisions, and taste for employers à la Card et al. (2018), which limit the elasticity of labor supply to wages. In the model, agents differ in entrepreneurial productivity and the amenities they could provide as employers. Every period they choose whether to leverage their productivity to open a business or to work for wages. Because workers value employer-specific amenities, entrepreneurs hold wage-setting power and can attract employees despite paying less than their marginal product. Entrepreneurs can also invest to improve their expected future productivity subject to a fixed cost. Through employer turnover, innovation, and labor supply decisions, the model generates a host of facts on firm dynamics that can be compared to the data.

Calibrated to firm-level micro-data for the Netherlands, the model reproduces cross-country differences in firm growth, innovation rate, and firm age structure through changes in the labor supply elasticity that mimic the estimated patterns of wage markdown across countries. Moreover, we show that differences in wage markdown alone can account for up to 42% of the observed variation in GDP per capita across countries.

In the model, labor market power slows firm dynamics and reduces aggregate income through three channels. The first channel is standard in models of neoclassical monopsony (Card et al., 2018; Dustmann et al., 2022) 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 relatively novel. Under imperfect competition in the labor market, both *selection into entrepreneurship* and *innovation decision* are altered: lack of competition makes amenities more important determinants of profits, allowing low-productivity agents to reap high benefits from entrepreneurship, and lowering the returns from investing in productivity. By penalizing high-productivity employers, labor market power acts as a skill-biased force in the labor market, similar to what has been shown for a wide array of size-dependent policies (Guner et al., 2008; Gourio and Roys, 2014; Garicano et al., 2016; Ando, 2021): both mechanisms keep firms inefficiently small and unproductive, reducing firm growth and aggregate output. Using our calibrated model, we quantitatively decompose each channel and find that at least one-third of the losses in income per capita caused by labor market power are attributable to distorted entrepreneurial decisions and lack of innovation.

This paper relates to recent work on the costs of labor market power. Berger et al. (2022) estimate the welfare losses from labor market power to be 6 percent of lifetime consumption in the US. Armangué-Jubert et al. (2024) find that labor market power can explain 15 percent of the difference in GDP per capita over the development ladder. Deb et al. (2022) show that a less competitive market structure lowered the average wage of low- and high-skilled workers in the US by 12 and 11 percent, respectively. Bachmann et al. (2022) show that monopsony leads firms to stay inefficiently small and invest less in marketing, and caused a 10 percent loss in aggregate productivity in East Germany. We contribute to this literature by showing that the lack of competitive pressure in the labor market distorts allocative efficiency, alters selection into entrepreneurship, and reduces firms' incentives to innovate, resulting in lower firm growth and lower aggregate productivity.

Our paper also belongs to the macro literature that focuses on how differences in frictions and distortions could generate the observed cross-country differences in income per capita. (e.g. Hsieh and Klenow, 2009; Bento and Restuccia, 2017; Da-Rocha et al., 2023; Guner and Ruggieri, 2022; Tamkoç and Ventura, 2024). We contribute to this literature by showing that differences in labor market competition can explain a significant fraction of the observed gaps in GDP per capita across countries.

The remainder of the paper goes as follows. In Section 2 we discuss cross-country evidence on firm dynamics, innovation, and labor market power. We introduce our model in Section 3. In Section 4 we describe the calibration strategy while in Section 5 we perform counterfactual experiments and discuss model mechanisms. We conclude in Section 6.

2 Stylized facts

In this section, we discuss how firm dynamics and local labor market competition vary across countries with different incomes per capita. For this purpose, we use 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, spanning more than 90 countries from 2006 to 2021. The data 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 capita in 2017 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. In what follows, we define a local labor market as a location-industry pair, where locations are the first administrative level of the country and industries are ISIC 3.1.

Panels A and B in Figure 1 report the average firm size growth and the average firm age across countries in our sample, ranked by their GDP per capita. Each dot refers to the average local labor market in a country. Firm size growth is computed as a log difference between the current and initial size, where the latter is defined as the number of employees recorded in the first year of operations. Similarly, we use the first year of operations to compute the average firm age.

Firms in countries with high GDP per capita grow faster in size over their life cycle and are older on average.[1] The average firm size growth is about 90 percent in countries with a GDP per capita of $20,000 and it increases to around 120 percent in countries with a GDP per capita of $60,000. Similarly, as we move from poorer to richer countries, the average firm age increases from 11 to almost 30 years. These facts replicate and extend those in Hsieh and Klenow (2014), who document higher size growth and a higher likelihood of survival of firms in the US compared to those in Mexico and India.

Panel C in Figure 1 reports the share of firms that innovate across countries. Like before, each dot refers to the average local labor market in a country. To measure innovation, we use the share of firms that report having conducted formal research and development activities.[2]

Firms in high GDP per capita countries are more likely to perform R&D, and to invest in innovation. As we move from poorer to richer countries, the share of

[1] Firms in richer countries growth faster along their life cycle even conditional on survival. See Appendix A.2.

[2] The question asked by WBES is "During last fiscal year, did this establishment spend on formal research and development activities, either in-house or contracted with other companies, excluding market research surveys?" We construct a binary variable for innovation taking value 1 if a firm reports a positive spending on formal research and development activities.

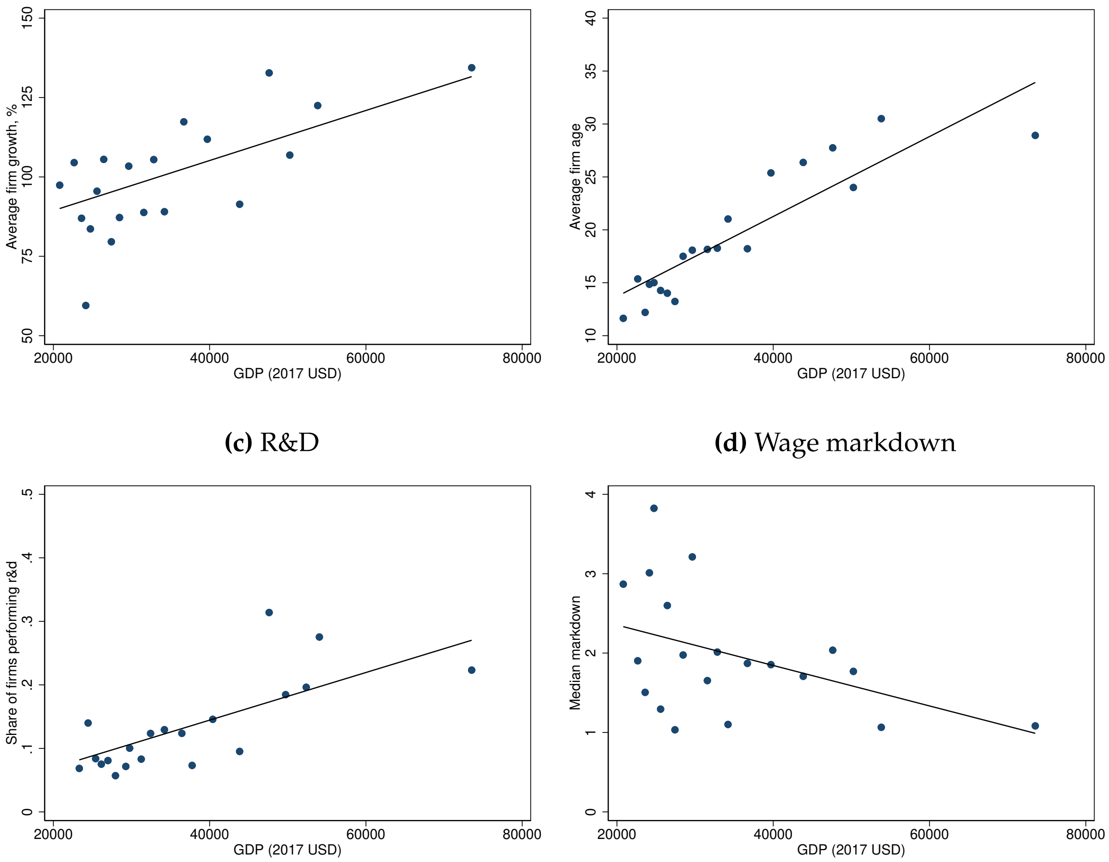
Figure 1: Firm dynamics, innovation, and markdown across countries

(a) Average firm size growth, unconditional

(b) Average firm age

(c) R&D

(d) Wage markdown



NOTES: Panel A is a binscatter plot of the average firm size growth across countries over their GDP per capita. Panel B shows a binscatter of the average firm age across countries over their GDP per capita. Panel C shows a binscatter of the share of firms that innovate across countries over their GDP per capita. Panel D shows a binscatter of the median markdown across countries over GDP per capita. Fitted lines are obtained from an auxiliary regression on GDP per capita. GDP per capita is expressed in 2017 USD.

firms that spend on R&D triples, from around 10 percent to 30 percent.[3] This evidence is consistent with Lederman and Maloney (2003), who document that R&D expenditure (measured as a share of GDP) is higher in richer countries, and it complements recent findings of Farrokhi et al. (2024), who document relatively low adoption of new technology in low-income countries.

[3]In Appendix A.3 we show that firms in richer countries are more likely to conduct both product and process innovation.

Finally, we compare the degree of local labor market competition across countries and use firm-level wage markdown as a proxy for labor market power. Specifically, we construct wage markdowns, μ_{it} for firm i at time t as a ratio between the firm-level marginal revenue product of labor and the wage paid (Brooks et al., 2021; Yeh et al., 2022), i.e.

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

Under a Cobb-Douglas assumption, we can express the marginal revenue product of labor as a share of its average revenue, i.e.

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

where β is the revenue elasticity of labor. We measure average revenues, y_{it}/ℓ_{it}, and average wage, w_{it}, using firm annual sales per number of employees and annual payroll per number of employees, respectively, while we estimate β separately for each country and year in the sample using a control function approach as in Levinsohn and Petrin (2003). We report details of the estimation procedure in Appendix A.4.

Panel D in Figure 1 scatters the median markdown in the average local labor market of countries in our sample against GDP per capita.[4]

Local labor markets are more competitive in richer countries, and firms charge lower markdowns. In countries with a GDP per capita of $20,000, we estimate a median markdown of 2.25 on average; that is, workers are paid about 50% less than their marginal product. These values fall in the range of estimates for middle-income countries obtained from other studies in the literature. For instance, Garcia-Louzao and Ruggieri (2023) estimate a labor supply elasticity for Lithuania (GDP per capita $23,065 in 2013) ranging between 0.7 and 0.9, which corresponds to wage markdowns between 2.1 and 2.4; Ogloblin and Brock (2005) document that male workers in Russia (GDP per capita of $25,933 in 2012) earn around 35.5% less than their potential competitive wage, corresponding to a wage markdown of 1.55.

[4] In Appendix A.4 we report average markdown across countries.

In high-income country, the estimated wage markdown is much lower. The median markdown is about 1.25 in countries with a GDP per capita of $60,000, which means workers are paid 20% less than their marginal product. The estimated wage mark-downs for high-income countries fall within the range of estimates of 17% and 24% provided by Azar et al. (2022) and Berger et al. (2022) for the United States. It also lies between 16% and 25%, the estimates obtained by Datta (2022) for the United Kingdom.

Finally, our evidence is consistent with Armangué-Jubert et al. (2024), who show that markdowns decrease with income per capita for countries with GDP per capita over $2,000. 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 estimates of wage markdowns for countries just above this threshold are consistent with their estimates for countries just below the threshold.

To summarize, firms grow faster and are more likely to innovate in richer countries, where local labor markets are more competitive. In the next section, we build a dynamic model of neoclassical monopsony that fits our stylized facts and use it to study how labor market power affects firm dynamics, innovation, and aggregate productivity.

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 defined over a ladder $\mathcal{Z} = [\underline{z}, ..., z_-, z, z_+, ..., \overline{z}]$, and amenities a defined over a subset $\mathcal{A}$ of the reals. 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_ν.[5]

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

[5] 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).

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, $1 - p_n$. 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:[6]

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

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:

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

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

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:

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

where

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

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. 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

$$\begin{aligned} &\max_{w_j} \pi_j(z_j, a_j) = z_j \ln(L_j) - w_j L_j - c_f \qquad (3)\\ &\textit{subject to} \quad L_j = L\Theta \exp\left(\epsilon^L \ln(w_j) + a_j\right) \end{aligned}$$

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 (9), (10) and (11), defined in Appendix B.1.
- 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.2.

3.4 Discussion

In the model, competition in the labor market operates as a "skill-biased" force, in the sense of favoring high-productivity entrepreneurs, and it does so through different channels.

To gain some insights, let us assume labor supply L is fixed and constant. 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.

Substituting the equilibrium employment choice into the labor supply function, we obtain the following equation for wage posted by firm j:

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

[7] See Autor et al. (2023) for a detailed discussion.

which implies a wage bill, $w_j L_j$, equal to $z_j \frac{\epsilon^L}{1+\epsilon^L}$, and a profit flow equal to

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

It is easy to see that profits reallocate from high- to low-amenities firms when the elasticity increases. Notice that:

$$\pi_j(z, \overline{a}) - \pi_j(z, \underline{a}) = z \left[\ln(L(z, \overline{a})) - \ln(L(z, \underline{a}))\right]$$

where $\overline{a}$ is sufficiently larger than $\underline{a}$. With a constant aggregate labor supply L, because labor reallocates away from high-amenities firms, i.e. $L(z, \overline{a})$ decreases while $L(z, \underline{a})$ increase with ϵ^L, then it must be that:

$$\frac{\partial[\pi_j(z, \overline{a}) - \pi_j(z, \underline{a})]}{\partial \epsilon^L} \leq 0, \tag{7}$$

By the same argument, it can be shown that profits reallocate from low- to high-productivity firms, i.e.

$$\frac{\partial[\pi_j(\overline{z}, a) - \pi_j(\underline{z}, a)]}{\partial \epsilon^L} \geq 0 \tag{8}$$

when $\overline{z}$ is sufficiently larger than $\underline{z}$.

Through reallocation of employment and profits across firm types and occupations, changes in labor market power have implications for selection into entrepreneurship and investment in R&D. With a low labor supply elasticity, agents with high amenities have wage-setting power as entrepreneurs and can make sufficient profits to compete in the market even with relatively low productivity. When labor supply elasticity increases, the competitive advantage shifts away from high-amenities firms and towards high-productivity firms, as shown by equations (7) and (8). This alters the decision to become entrepreneurs, improving selection in favor of high-productivity agents. It also alters the decision to innovate, which becomes more profitable and more affordable for high-productivity firms, resulting in higher firm growth, higher productive efficiency, and higher output per capita.

In the next section, we use our model to quantify how much each mechanism, i.e. labor allocation across employers, selection into entrepreneurship, and innovation decision, contribute to fostering firm dynamics and productivity, allowing labor supply to react to changes in labor market power.

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_ν, 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.

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. 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%

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, their values, and the target or source used.

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.

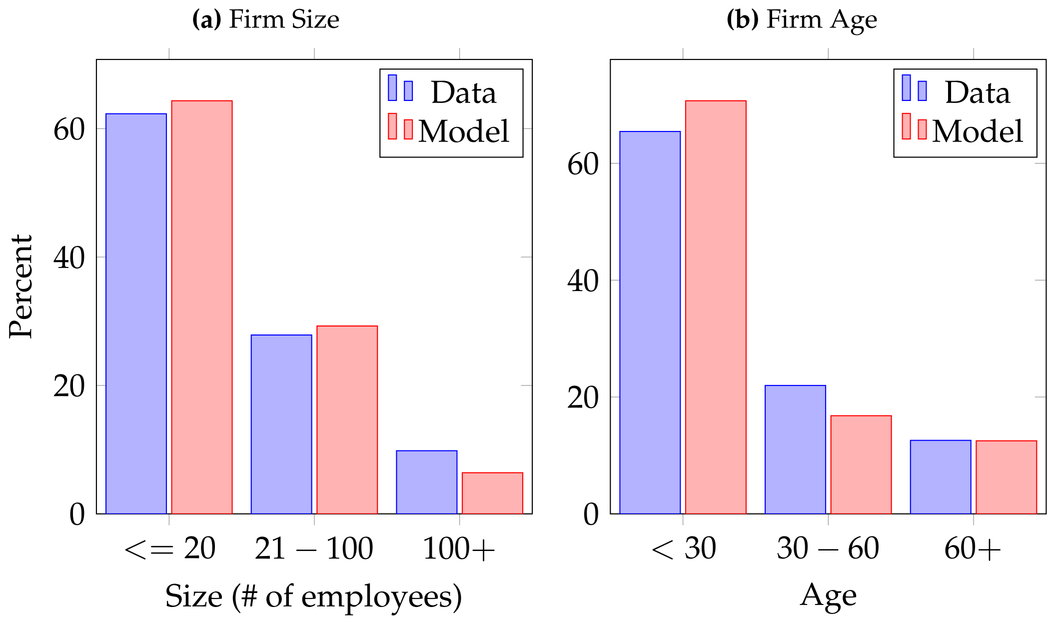
and it informs the model about the productivity dynamics of investors, p_i whereas the average firm age, 28.93 y.o., will discipline the productivity dynamics of non-investors, p_n through entry and exit into entrepreneurship. Finally, the dispersions in entrepreneurial talents at entry, σ_z, and amenities, 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.[8]

The model also replicates the empirical firm size and age distributions observed in the Netherlands despite neither being part of the targeted moments. Panel A of Figure 2 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 em-

[8]Table B1 in Appendix B.3 reports the list of targeted moments and their model counterpart.

ployees, both in the model and the data. Panel B reports the percentage of firms across different firm age groups in the data and 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.

Figure 2: Firm Size and Firm Age - Model vs Data

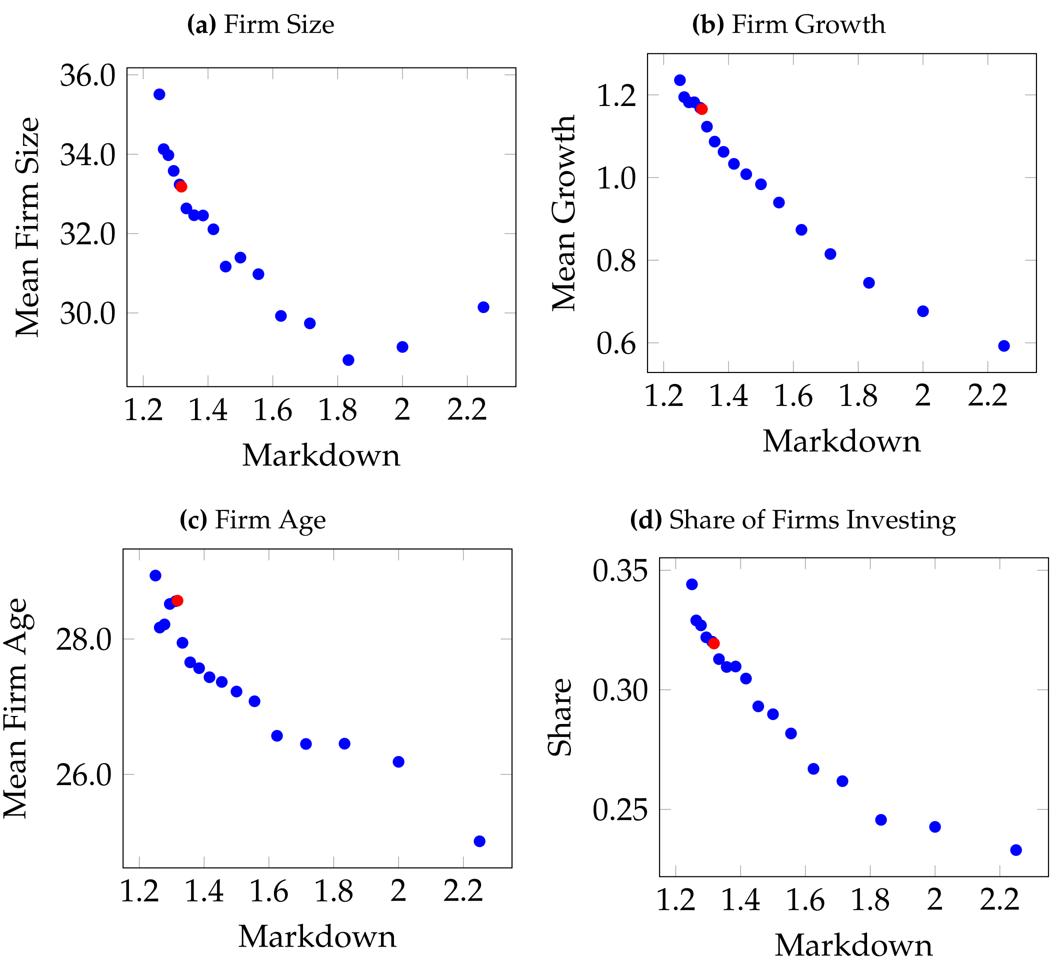


NOTES: Blue bars represent the shares of firms over firm size and firm age groups found in the data, red bars show the corresponding shares predicted by the model.

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 3: 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.

Figure 3 reports the average firm size (panel A), average life-cycle firm growth (panel B), average firm age of operating firms (panel C), and the share of firms investing in R&D (panel D), for economies with different degrees of labor market competition. The red dot refers to the benchmark economy, the Netherlands. The blue dots refer to counterfactual scenarios.

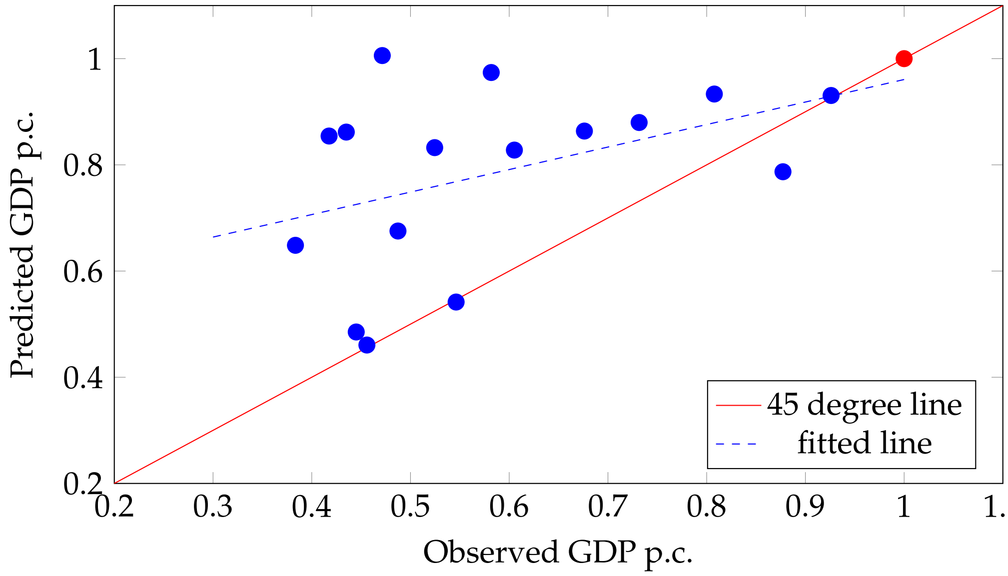
The average firm size reduces as the labor market becomes less competitive (panel A). Lower labor supply elasticity reduces the average firm size from approximately 42 employees to around 30. Labor market power also affects firm dynamics over the life cycle. Reducing labor market competition leads to 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%.

In the model, firms survive longer and are more likely to innovate when the labor market is more competitive. As we increase the labor supply elasticity 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 labor market power is in generating output dispersion in our sample of countries. Figure 4 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 aggregate output. 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 a value of 0.42. We interpret it as the ability of the model to 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, 2017; 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).

Figure 4: Cross-Country Income Differences: Model vs Data



NOTES: Each blue dot compares the observed GDP p.c. from Panel D in Figure 1 to the predicted GDP p.c. obtained by changing the value of ϵ^L to match the corresponding markdown in the data. Both observed and predicted GDP p.c. are expressed relative to the GDP p.c. of the Netherlands, in red.

5.1 Mechanisms

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 vs. $54,000); 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 3.318).

Table 3 reports various outcomes for benchmark and counterfactual economies (columns 1 and 2, respectively), and compares the latter to their empirical counterparts (column 3). Compared to the Netherlands, the average size of firms is smaller in Greece (18 vs 33 employees), firms grow less over the life cycle (68% vs 117%), have a lower likelihood of surviving (the average age is 19 years vs

Table 3: The Netherlands vs Greece

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

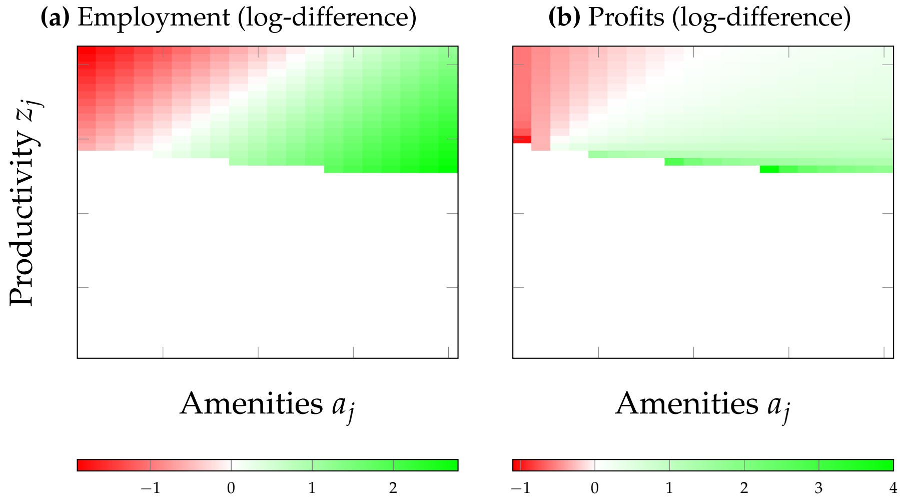
NOTES: Column (1) reports the average life-cycle firm growth, the average firm age, the share of entrepreneurs who innovate, and the value of GDP p.c. in the benchmark economy (Netherlands). Column (2) shows the same model-based moments in a counterfactual economy where ϵ^L is chosen to match the median markdown observed in Greece (leaving other parameters unchanged). Column (3) reports the empirical counterparts of these moments for Greece. Column (4) reports how much (%) of the difference between the Netherlands and Greece is explained by differences in labor supply elasticity.

29), and are less likely to invest in productivity innovation (11% vs. 32%). Differences in labor market competition can explain 15% of the differences in firm size, account for 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, respectively.

Why does firm dynamics slow down when labor markets are less competitive? Figure 5 shows how firm-level employment (Panel A) and profits (Panel B) change when we move from the benchmark (Netherlands) to the counterfactual (Greece) economy. Green areas refer to firms with states (z_j, a_j) expanding in size and making higher profits when we reduce the labor supply elasticity, ϵ^L. Red areas refer to firms shrinking and losing profits. As discussed in Section 3.4, labor reallocates to high-amenities firms and away from high-productive, low-amenity firms when labor market competition is weaker. As the elasticity of labor supply reduces, the relative importance of amenities increases, workers become less responsive to wage differences, and lack of competition pushes firms to post wages farther from the marginal revenue product of labor. As a result, profits increase for low-productivity high-amenity firms, allowing them to survive in the market, distorting allocative efficiency.

Changes in employment and profits also alter entrepreneurial and innovation

Figure 5: Reallocation of Labor and Profits



NOTES: Panel A shows the log-difference in firm-level employment for firms with different levels of firm productivity and amenities, between benchmark (the Netherlands) and counterfactual (Greece) economies. Panel B shows the log difference in firm-level profits.

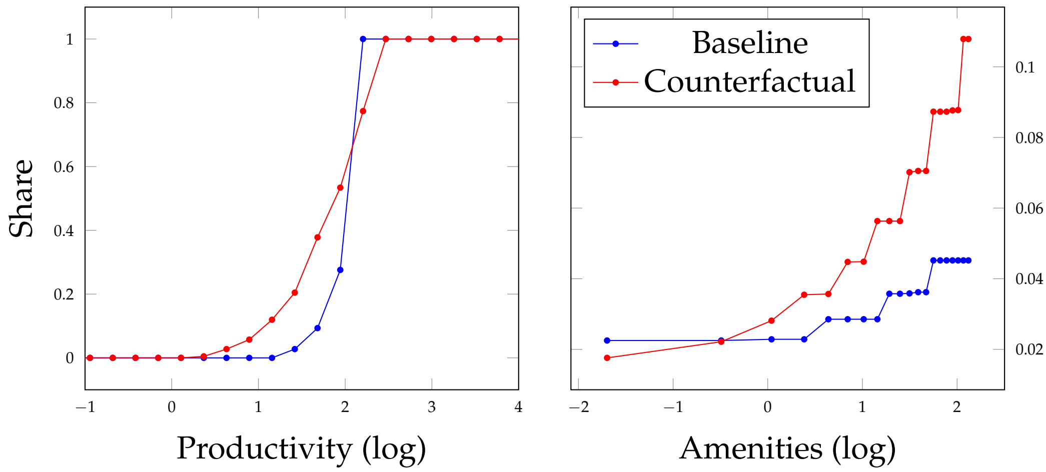
decisions. Figure 6 shows the share of agents by level of productivity (Panel A) and amenities (Panel B) that choose to become entrepreneurs in the benchmark (blue line) and the counterfactual economy (red line). Similarly, Figure 7 shows how the share of entrepreneurs that conduct R&D by levels of productivity (panel A) and amenities (panel B) in the benchmark (blue line) and the counterfactual economy (red line).[9]

In the model, agents choose whether to become entrepreneurs or wage workers aware of the equilibrium labor supply and demand curves. When ϵ^L is low, and the relative importance of amenities is higher, agents with low entrepreneurial productivity but high amenities can attract workers despite paying lower wages, Hence they anticipate being able to make net profits beyond what they could earn as wage workers, and choose to do so by self-selecting into entrepreneurship. Similarly, when ϵ^L is low and the role of productivity in shaping profits is weaker, returns to innovation diminish. This, together with the reallocation of profits towards high amenities and low-productivity firms,

[9]In Appendix B.4 we report the associated policy functions for entrepreneurship and innovation.

Figure 6: Share of Entrepreneurs

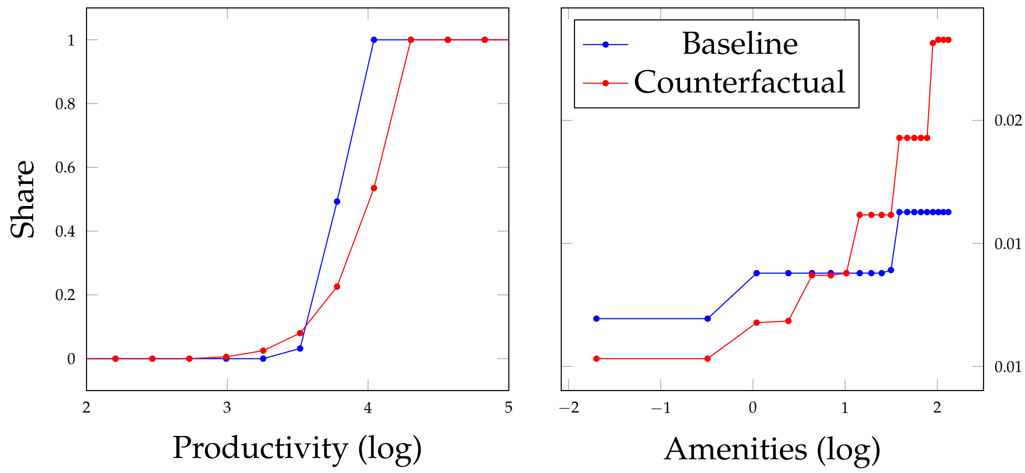
(a) Over Productivity Levels | **(b)** Over Amenities Levels



NOTES: The blue lines show the share of agents that become entrepreneurs by level of productivity (Panel A) and level of amenities (Panel B) in the benchmark (blue line). and counterfactual (red line) economy. The benchmark economy refers to the Netherlands. The counterfactual economy refers to an economy where ϵ^L is chosen to match the median markdown observed in Greece (leaving other parameters to their benchmark values).

Figure 7: Share of Entrepreneurs that Innovate

(a) Over Productivity Levels | **(b)** Over Amenities Levels



NOTES: The blue lines show the share of entrepreneurs that innovate by level of productivity (Panel A) and level of amenities (Panel B) in the benchmark (blue line). and counterfactual (red line) economy. The benchmark economy refers to the Netherlands. The counterfactual economy refers to an economy where ϵ^L is chosen to match the median markdown observed in Greece (leaving other parameters to their benchmark values).

reduces R&D investment, particularly for high-productivity firms. By favoring high-productivity firms, labor market competition operates a skill-biased force.

Finally, we decompose how much each margin, meaning, allocation of labor, selection into entrepreneurship, and investment in R&D, contribute to differences in output per capita between benchmark and counterfactual. We do it using two alternative experiments. In the first one, we change ϵ^L to the level observed in Greece while fixing entry and investment policy functions to the ones in the benchmark economy, i.e. we solve the model for the counterfactual keeping selection into entrepreneurship and investment in R&D fixed. In the second alternative scenario, we perform the same exercise while fixing only the entry policy function from the benchmark, i.e. we solve the model for the counterfactual keeping only selection into entrepreneurship at the benchmark level.

Table 4: Sources of output losses

	Benchmark (1)	Counterfactual with Benchmark Entry and Investment (2)	Counterfactual with Benchmark Entry (3)	Counterfactual (4)
GDP p.c.	1.00	0.78	0.73	0.65
%	0	63	77	100

NOTES: Column (1) reports the value of GDP p.c. in the benchmark economy (Netherlands). Column (2) shows the value of GDP p.c. in a counterfactual economy where ϵ^L is chosen to match the median markdown observed in Greece (leaving other parameters unchanged), keeping entry and investment policy fixed at their benchmark level. Column (3) shows the value of GDP p.c. in a counterfactual economy where ϵ^L is chosen to match the median markdown observed in Greece (leaving other parameters unchanged), keeping entry policy fixed at their benchmark level. Column (4) shows the value of GDP p.c. 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.

Table 4 reports the results of this decomposition exercise. Around two-thirds of the losses to income per capita induced by higher labor market power can be attributed to changes in employment allocation, keeping innovation policy and selection into entrepreneurship unchanged. About 15 percent of the output losses are explained by the distortion to innovation policy, while the remaining 25 percent can be attributed to distorted selection into entrepreneurship.

These findings bridge the gap between the estimates of the cost of labor market power (Berger et al., 2022; Amodio et al., 2022; Armangué-Jubert et al., 2024) and the dynamic inefficiency cost studied in models of misallocation (Restuccia and Rogerson, 2017; Guner et al., 2018; Guner and Ruggieri, 2022). By altering investment and firm growth, our results suggest that losses from labor market power may be greater than those estimated by previous studies that focus solely on the static labor allocation effect.

6 Conclusion

This paper studies how labor market power affects firm dynamics and aggregate efficiency across countries. We do it using a general equilibrium model of labor market monopsony featuring endogenous entrepreneurial choice, dynamic firm innovation decisions, and taste shocks for employers that endow them with wage-setting power. Calibrated to the Netherlands, the model reproduces cross-country differences in firm growth, innovation rate, and firm age structure through changes in labor supply elasticity.

Through the lens of the model, we find that the differences in labor market power can explain up to 42 percent of differences in income per capita across middle- and high-income countries, one-third of which can be attributed to distorted selection into entrepreneurship and lower innovation rates. 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 Sample summary and descriptive statistics

Table A1: Harmonized WBES sample merged with GDP per capita in 2017 USD.

Country	Survey Waves	Num. Obs.
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
Netherlands	2020	808

Continued on next page

Table A1: Harmonized WBES sample merged with GDP per capita in 2017 USD.

Country	Survey Waves	Num. Obs.
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

Table A.1 lists the countries in the sample, their survey waves, and the number of observations recorded. Table A2 reports summary statistics for the variables used in Section 2.

Table A2: Summary statistics

Statistics	Mean	Median	SD	P25	P75
Firm size	38.29449	34.03288	29.86888	25.6522	41.07696
Firm size growth, %	100.7409	106.6709	26.61563	83.91069	116.8127
Firm age (years)	19.13966	17.04539	6.387424	13.86408	23.69623
Firm performing R&D	.133104	.1054764	.1003964	.0680691	.1753179
Firm performing process innovation	.2434614	.1926234	.1641043	.1066701	.3168902
Firm performing produc innovation	.3665908	.3599968	.2081535	.1990438	.493611
Sales (log)	14.01801	13.97619	.735148	13.57228	14.57004
Material expenditure (log)	12.72644	12.68444	.9570056	12.09132	13.50415
Capital expenditure (log)	12.66521	12.61433	.8513778	11.96849	13.43724

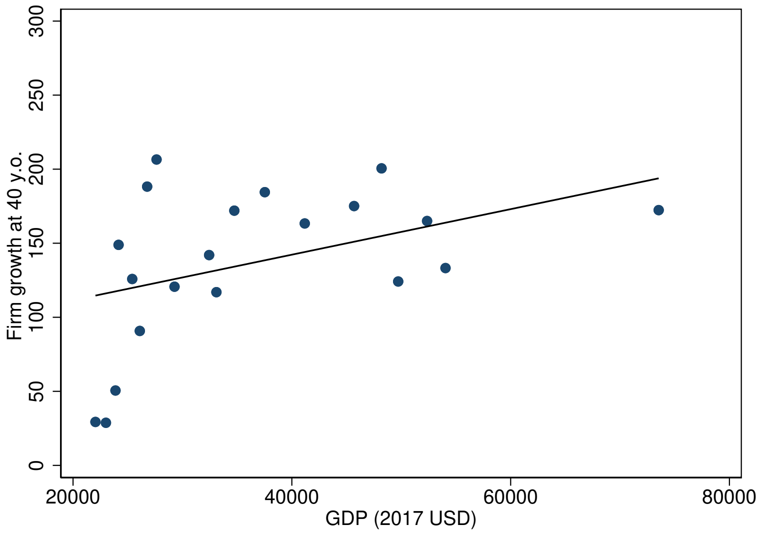
NOTES: Firm size to the current number of employees. Firm size growth is computed as the log difference between the current number of employees and the number of employees recorded in the first year of operations. Capital expenditure refers to the cost for the establishment to re-purchase all of its machinery. Sales refer to the establishment's total annual revenues Material expenditure refers to the cost of raw materials and intermediate goods used in production in the last fiscal year. Sales, material, and capital expenditure are deflated using the US GDP deflator and expressed in 2009 USD.

A.2 Firm Growth across Countries

Figure A1 complements Figure 1 from the main text and it reports the cross-country average firm growth conditional on firms that are 40 years old. The average firm growth is higher in richer countries even when conditioned on firm age, and it increases from around 50% in countries with a GDP per capita of $20,000 to around 150% in countries with a GDP per capita above $60,000.

Figure A1: Firm dynamics over development

(a) Average firm size growth, 40 years



NOTES: The Figure binscatters the average firm size growth at 40 years of operations across countries over their GDP per capita. The fitted line is obtained from an auxiliary regression on GDP per capita. GDP per capita is expressed in 2017 USD.

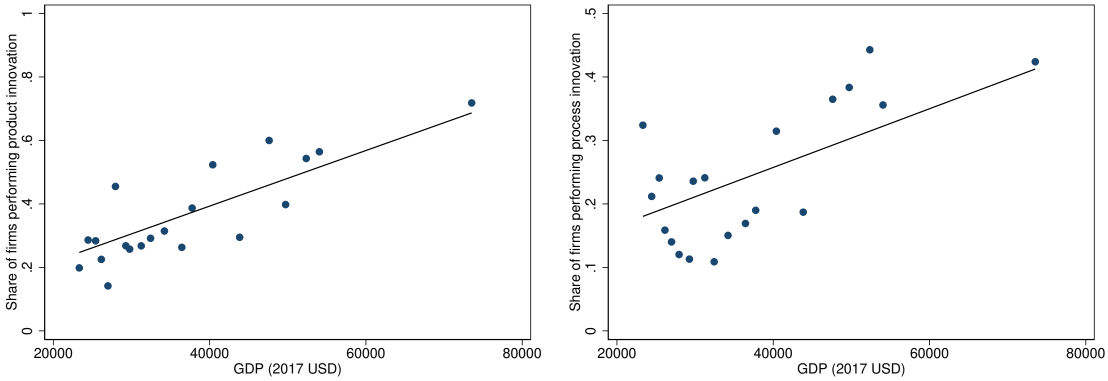
A.3 Innovation across Countries

Figure A2 complements Figure 1 in the main text and it reports the share of firms performing product innovation (panel A) and process innovation (panel B) across countries with different GDP per capita.

Regardless of the measure of innovation used, firms innovate more in richer countries: as we move from middle to high-GDP per capita countries, the share of firms performing product innovation increases from 20 to 80%. Similarly, the share of firms performing product innovation increases from 20 to 40%.

Figure A2: Firm innovation over development

(a) Product innovation **(b)** Process innovation



NOTES: Panel A binscatters the share of firms that conduct product innovation across countries over their GDP per capita. Panel B binscatters the share of firms that conduct process innovation across countries over their GDP per capita. Fitted lines are obtained from auxiliary regressions on GDP per capita. GDP per capita is expressed in 2017 USD.

A.4 Wage markdown across Countries

We measure labor market power at the firm-year level by comparing the firm's marginal revenue product of labor to the wage paid (Amodio et al., 2024). To do so, we first assume a Cobb-Douglas revenue production function specification,

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

where y_{it} is firm sales, ℓ_{it} denotes number of employees, k_{it} is capital, m_{it} materials 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). 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. This involves estimating the following equation:

$$\log y_{it} = \alpha + \beta \log \ell_{it} + \phi(\ell_{it}, k_{it}, m_{it}) + \epsilon_{it}$$

Where $\phi(\ell_{it}, k_{it}, m_{it}) = \alpha k_{it} + \gamma \log m_{it} + F_M^{-1}(\ell_{it}, k_{it}, m_{it})$, with $F_M^{-1}(\ell_{it}, k_{it}, m_{it})$ being the inverse of the input demand function for materials with respect to ω_{it}. We proxy for this unspecified function in a partially linear model (Robinson, 1988) as in Levinsohn and Petrin (2003). 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,

$$\mu_{it} = \frac{\text{MRPL}_{it}}{w_{it}} \quad \text{where} \quad \text{MRPL}_{it} = \frac{\partial y_{it}}{\partial \ell_{it}} = \hat{\beta} \frac{y_{it}}{\ell_{it}}$$

Table A3 reports the statistics for the distribution of estimated country-year revenue elasticities of employment, $\hat{\beta}$.

Table A3: Estimated revenue elasticity of employment

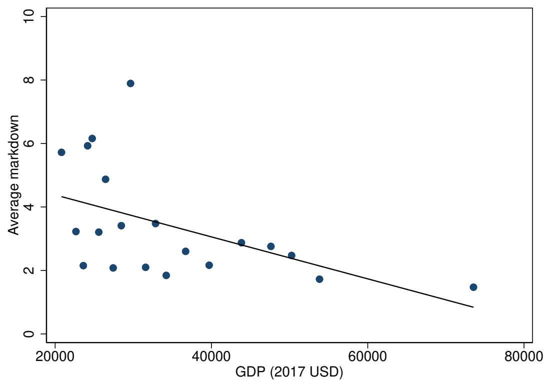
Statistics	Mean	Median	SD	P25	P75
$\hat{\beta}$	0.4472	0.4110	0.2042	0.3267	0.5557

NOTES: This table reports summary statistics for the distribution of estimated country-year revenue elasticities of employment, $\hat{\beta}$

The mean estimates for the elasticity is 0.4472. The distribution of estimates is not excessively dispersed across countries and years: the standard deviation is 0.2042 and the interquartile range is 0.2283.

Figure A3 complements Figure 1 in the main text and shows that also the average markdown across countries with different GDP per capita. The average markdown is relatively larger than the median (see Figure **??** in the main text). In meddle-income countries (with a GDP per capita of $20,000) the average markdown is about 4, which implies an elasticity of labor supply of about 0.33. In richer countries (with GDP per capita of $60,000), the average markdown is around 1.5, which implies an elasticity of labor supply of about 2.

Figure A3: Average wage markdown over development



NOTES: This figure binscatters the mean markdown across countries over GDP per capita. The fitted line is obtained from auxiliary regressions on GDP per capita. GDP per capita is expressed in 2017 USD.

B Model Appendix

B.1 Equilibrium distribution

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

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

$$
\begin{aligned}
\Omega(\underline{z},a)' = {} & (1-\delta_w)(1-p_n)[(1-\rho^z(\underline{z},a))\rho^e(\underline{z},a)+(1-\rho^e(\underline{z},a))]\Omega(\underline{z},a) \\
& +(1-\delta_w)(1-p_i)\rho^z(\underline{z},a)\rho^e(\underline{z},a)\Omega(\underline{z},a) \\
& +(1-\delta_w)(1-p_n)[(1-\rho^z(\underline{z}_+,a))\rho^e(\underline{z}_+,a)+(1-\rho^e(\underline{z}_+,a))]\Omega(\underline{z}_+,a) \\
& +(1-\delta_w)(1-p_i)\rho^z(\underline{z}_+,a)\rho^e(\underline{z}_+,a)\Omega(\underline{z}_+,a) \\
& +\delta_w\Psi(\underline{z},a)
\end{aligned} \tag{11}
$$

B.2 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 (9) and (10) and (11) to get $\Omega(z,a)^{i+1}$, if not sufficiently close to $\Omega(z,a)^i$ return to step 2.

B.3 Model Fit

Table B1 reports the list of targeted moments and their moment counterparts in the benchmark estimation. The sum of squared deviations between empirical and simulated moments is equal to 2.9%.

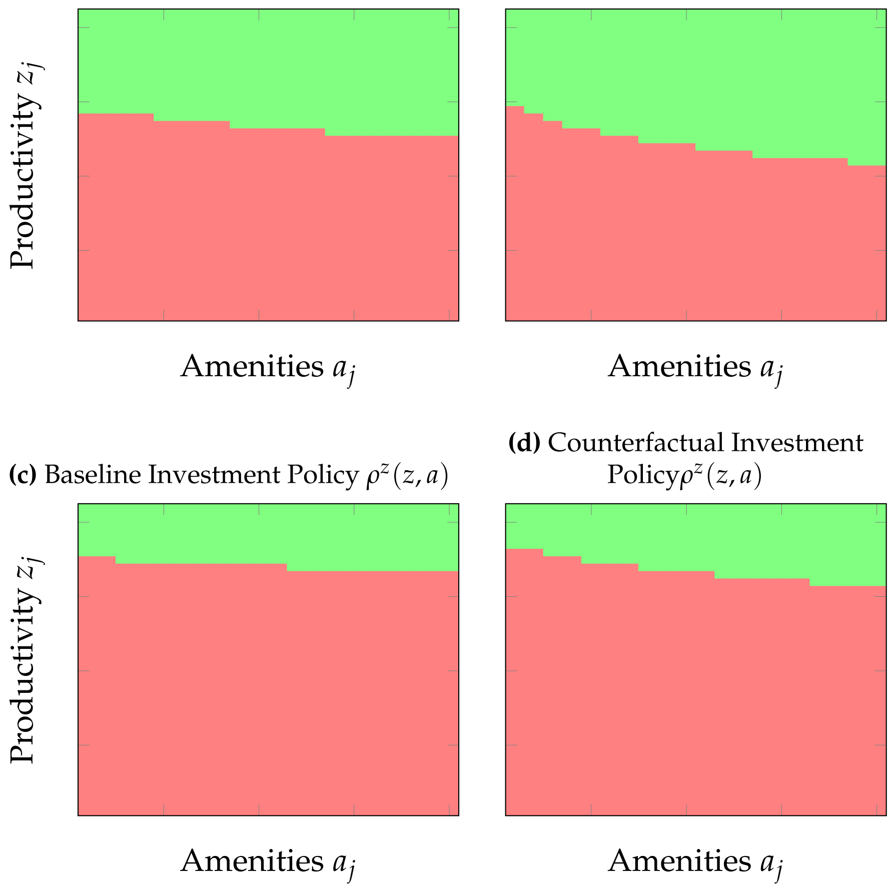
Table B1: Model fit

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

B.4 Counterfactual Policy Functions

Figure B1 shows the entry into entrepreneurship and investment policy functions in the baseline and counterfactual scenarios.

Figure B1: Policy Functions



(a) Baseline Entrepreneurship Policy $\rho^e(z, a)$

(b) Counterfactual Entrepreneurship Policy $\rho^e(z, a)$

(c) Baseline Investment Policy $\rho^z(z, a)$

(d) Counterfactual Investment Policy$\rho^z(z, a)$

Notes: Panels A and B show the policy function for entrepreneurship in the baseline and the counterfactual respectively. Panels C and D show the policy function for investment in the baseline and counterfactual respectively.