Online Appendix

Labor Market Power and Development

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Model Appendix

A1: Discrete Distributions of Potential Entrants

Following Eaton et al. (2012) and Amodio et al. (2022), let the primitive, or underlying, distribution of firm productivities be a Pareto with shape parameter α and scale parameter θ:

$$f(x;\alpha) = \frac{\alpha}{x^{\alpha+1}}.$$

Given some number of potential entrants $\bar{E}$, we first draw the productivity of the most productive firm denoted A^1, which by the Fisher–Tippett Theorem (Fisher and Tippett, 1928) follows a scaled Fréchet distribution with shape α and scale $\bar{E}^{1/\alpha}$:

$$f(x;\alpha,\theta) = \frac{\alpha}{\theta}\left(\frac{x}{\theta}\right)^{-\alpha-1}\exp(-(x/\theta)^{-\alpha}).$$

It follows that if we define:

$$U^k = \frac{1}{\bar{E}^{1/\alpha}}\left(A^k\right)^{-\alpha},$$

U^1 is distributed with an exponential:

$$F(u) = 1 - \exp(-u).$$

Given U^1, U^k for $k > 1$ are obtained by exploiting the fact that:

$$\Pr[U^{k+1} - U^k \leq u] = 1 - \exp(-u),$$

as shown by Eaton and Kortum (2010).[1]

[1] This can be found here: `https://www.blogs.uni-mainz.de/fb03-economics-macro/files/2018/11/EatonKortum030410.pdf`

Given the full vector $\mathbf{U}$, the vector of productivities $\mathbf{A}$ is obtained by reversing the transformation from A^k to U^k.

A2: Solution Algorithm

Given a set of parameters $\{\alpha, \theta, a, b, L, \epsilon^L, \bar{E}, c_e\}$, a distribution of firm productivities $\Phi(z_j; \alpha, \theta)$ and distribution of firm amenities $\Psi(a_j; a, b)$, an algorithm to solve for the equilibrium works as follows:

1. Given the number of potential entrants $\bar{E}$ and the distributions $\Phi(z_j)$ and $\Psi(a_j)$, draw the vectors of productivities $\vec{\mathbf{A}}$ and amenities $\vec{\mathbf{a}}$ of potential entrants.

2. Set the initial number of firms equal to the number of potential entrants $J^{x=-1} = \bar{E}$.

3. Solve the fixed point of wage schedules and rank firms by profitability, use the positive profit threshold to guess the starting value $J^{x=0}$.

4. With the current value of J^x, solve the fixed point of wage schedules:

   (a) Guess the vector of wages $\vec{\mathbf{w}}^{i=0} = [w_1^{i=0}, w_2^{i=0}, ..., w_J^{i=0}]$.

   (b) For each firm $j \in J$:

      i. Compute λ_j using equation 2.

      ii. Solve the profit maximization problem using the current vector $\vec{\mathbf{w}}$ and associated value of λ_j to obtain an updated wage w_j^{i+1}.

      iii. Adjust the updated wage for smooth convergence using: $w_j^{i+1} = \delta w_j^{i+1} + (1-\delta) w_j^i$ and some $\delta \in (0, 1)$.

   (c) If $\vec{\mathbf{w}}^i$ and $\vec{\mathbf{w}}^{i+1}$ are sufficiently close, the Nash Equilibrium has been found. If not, return to step (b).

5. Given the fixed point of wage schedules $\vec{\mathbf{w}}^*$, compute the vector of firm profits $\vec{\boldsymbol{\pi}}$ and:

   - If $\pi_j \geq 0 \; \forall j$ and $J^{x-1} \neq J^x + 1$ set $J^{x+1} = J^x + 1$ and return to step 4.

- If $\pi_j \geq 0 \; \forall j$ and $J^{x-1} = J^x + 1$ stop with J^x.
- If $\pi_j \neq 0 \; \forall j$ and $J^{x-1} \neq J^x - 1$ set $J^{x+1} = J^x - 1$ and return to step 4. The firm removed is the firm with the lowest competitiveness.[2]
- If $\pi_j \neq 0 \; \forall j$ and $J^{x-1} = J^x - 1$ stop with J^{x-1}.

A3: Proofs to Proposition 2

Equation (6) in the main text shows that the dispersion of log employment across firms can be written as:

$$\text{var}[\ln L_j] = \left(\frac{\epsilon^L}{1+\epsilon^L}\right)^2 \text{var}[\ln(z_j)] + \left(\frac{1}{1+\epsilon^L}\right)^2 \text{var}[a_j].$$

Taking the first derivative with respect to ϵ^L we get:

$$\frac{\partial \text{var}[\ln L_j]}{\partial \epsilon^L} = \frac{[2\epsilon^L(1+\epsilon^L)^2 - 2(\epsilon^L)^2(1+\epsilon^L)]}{(1+\epsilon^L)^4}\text{var}[\ln(z_j)] - \frac{2(1+\epsilon^L)}{(1+\epsilon^L)^4}\text{var}[a_j].$$

The variance of log employment $\text{var}[\ln L_j]$ increases with the labor supply elasticity ϵ^L as long as $\frac{\partial \text{var}[\ln L_j]}{\partial \epsilon^L} > 0$, meaning:

$$\begin{aligned}
[2\epsilon^L(1+\epsilon^L)^2 - 2(\epsilon^L)^2(1+\epsilon^L)]\text{var}[\ln(z_j)] - 2(1+\epsilon^L)\text{var}[a_j] &> 0 \\
[\epsilon^L(1+\epsilon^L) - (\epsilon^L)^2]\text{var}[\ln(z_j)] - \text{var}[a_j] &> 0 \\
[\epsilon^L + (\epsilon^L)^2 - (\epsilon^L)^2]\text{var}[\ln(z_j)] - \text{var}[a_j] &> 0 \\
\epsilon^L \text{var}[\ln(z_j)] - \text{var}[a_j] &> 0 \\
\text{var}[\ln(z_j)] &> \frac{\text{var}[a_j]}{\epsilon^L}
\end{aligned}$$

The last condition implies that the variance of log employment $\text{var}[\ln L_j]$ increases with the labor supply elasticity ϵ^L as long as log productivity is sufficiently dispersed across firms. This completes the proof.

[2]This ranking comes from step 3.

Data Appendix

B1: Data Sources

We use data from four different sources: the World Bank World Development Indicators, the World Bank Enterprise Surveys, Poschke (2018), and Bento and Restuccia (2017).

World Bank World Development Indicators are a collection of internationally comparable statistics about countries' development. Details can be found in `https://datatopics.worldbank.org/world-development-indicators/`. The only variable we use from these indicators is GDP per capita, PPP, in 2017 international dollars (NY-GDP-PCAP-PP-KD).

World Bank Enterprise Surveys are a series of establishment-level surveys conducted in over 130 countries that are representative of countries' private formal sector. Details are provided in `https://www.enterprisesurveys.org/en/enterprisesurveys`. We use data provided in two different datasets: "Firm-Level-TFP-Estimates-and-Factor-Ratios-Data-and-Documentation.zip" (WBES-1) and "StandardizedNew-2006-2023-core4.zip" (WBES-2).

From WBES-1 we use the following variables:

- *idstd*: unique firm identifier.
- *wt*: weight according to median eligibility.
- *country_official*: the official country name.
- *year*: year of the survey wave.
- *d2_gdp09* - deflated total sales in 2009 USD.
- *n2a_gdp09* - deflated total labor cost in 2009 USD.

From WBES-2 we use the following variables:

- *idstd*: unique firm identifier.
- *wt*: sampling weight.

- *stra_sector*: stratification sector.
- *d1a2*: 4-digit ISIC code of main product/service sold by the firm.
- *a2x*: stratification region.[3]
- *a14y*: year.
- *a17*: perception about the truthfulness regarding provided figures.
- *b1*: legal firm status.
- *b5*: year of firms' start of operations.
- *d3a*: percentage of national sales.
- *size_num*: number of employees.
- *e30*: obstacles from informal competition (4 categories).

From the WBES-2 data, we construct the following controls:

- exporter: binary variable that equals one if more than 5% of the firm's sales are abroad.
- foreign: binary variable that equals one if more than 50% of the firm is owned by foreign entities.
- public: binary variable that equals one if the firm is a publicly traded company.
- firm age group: categorical variable that groups firms into 1) 5 or fewer years since the beginning of operations, 2) between 6 and 15 years since the beginning of operations, and 3) over 15 years since the beginning of operations.

The WBES has some limitations. First, the number of observations is limited and ranges from around 150 for small economies, such as those of island states in the Caribbean, to around 600 for medium economies, such as Sweden, and

[3]See the WBES sampling note for details on stratification `https://www.enterprisesurveys.org/en/methodology`.

up to around 2000 for large economies, such as Germany. Table **??** in Appendix B3 shows the number of observations in each country in the sample, as well as the years of each survey wave and the level of GDP per capita. Second, the WBES does not cover the informal sector, which is more prevalent in low and middle-income countries, and it only surveys establishments with more than 5 employees. Finally, the number of high-income countries in the WBES is small (the US, for example, is not in the WBES).

Bento and Restuccia (2017). We use the mean firm size data provided in Bento and Restuccia (2017) for 134 countries.

Poschke (2018). We use the inter-quartile range of the firm size distribution provided in Poschke (2018) for 44 countries.

B2: Sample and Construction of Moments

For each target, we merge the source data for the moment of interest with the GDP per capita data. We exclude countries with a GDP per capita under $2000.

B2.1: Firm Size Wage Premium

We use WBES data for the construction of the firm-size wage premium targets. We use establishments' total cost of labor and the number of employees to compute the average wage in each establishment. Interviewers are asked to evaluate the truthfulness of the figures provided on a scale of 1) taken directly from establishment records, 2) estimates computed with some precision, 3) are arbitrary and unreliable numbers, and 4) are a mixture of estimates and records. We keep responses rated as either 1, 2, or 4 to exclude unreliable data. Finally, the data are winsorized at the country level by establishment wages; we drop the top and bottom 2.5% of values to exclude possible outliers.

We first estimate equation (8) separately for each country via OLS, controlling for year, region, and sector fixed effects, to obtain a set of possibly biased estimates of the firm-size wage premium. Due to limited sample sizes, we use the World Bank's strata regions and sectors as controls, which ensures that each country-region-sector has sufficient observations.

We then merge the resulting estimates for each country with its GDP per capita level and run the following auxiliary regression to obtain predicted levels of the firm-size wage premium along the development path:

$$\hat{\beta}_i = \alpha_1 + \alpha_2 \ln(GDPpc_i) + v_i. \tag{1}$$

Figure 1 (Panel E) shows the country-level estimates from the first set of regressions as well as the fitted line from the auxiliary regression and the points used as targets at each of the 4 stages of development. The Figure also shows our first suggestive finding: the firm size wage premium is decreasing in development. This finding is robust to a wide set of specifications and controls, as shown in Table B1.

B2.2: Mean Firm Size

While it is possible to calculate the average firm size using the WBES data, we use data from Bento and Restuccia (2017) as it provides better coverage for high-income countries. Furthermore, the samples in the WBES are restricted to firms with more than 5 workers. Bento and Restuccia (2017) harmonize census and representative survey data from 134 countries to construct comparable firm-size statistics across countries. We winsorize the data to exclude possible outliers by dropping the top and bottom 2.5% of values. We merge their data, winsorized to exclude possible outliers, with our GDP per capita data from the World Bank's World Development Indicators and run the following regression to obtain an OLS line of best fit and point estimates of mean firm size at the 4 stages of development:

$$\bar{\ell}_i = \alpha_1 + \alpha_2 \ln(GDPpc_i) + v_i. \tag{2}$$

We replicate their finding that average firm size is increasing in development, as shown in Figure 1 (Panel B), together with the fitted line and the point estimates that will be used as targets in the model estimation. Table B2 shows the result of estimating equation (2) used to plot the line of best fit and to compute the targets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
log(GDPpc)	-0.0256	-0.0222	-0.0152	-0.0255	-0.0274	-0.0256	-0.0251	-0.0158	-0.0108	-0.0218	-0.0228	-0.0111	-0.015	-0.005
	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.009)	(0.008)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	No	No	No	No	No	Yes	No	No	Yes	No	Yes
Exporter FE	No	No	No	Yes	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Foreign-Owned FE	No	No	No	No	Yes	No	No	No	No	No	Yes	Yes	Yes	Yes
Informal Competition FE	No	No	No	No	No	Yes	No	No	No	No	No	No	Yes	Yes
Publicly-Traded FE	No	No	No	No	No	No	Yes	No	No	No	No	No	Yes	Yes
Firm Age Group FE	No	No	No	No	No	No	No	Yes	No	No	No	No	Yes	Yes
Constant	0.3068	0.2734	0.1978	0.2992	0.3161	0.3019	0.2999	0.2023	0.1548	0.2627	0.2661	0.1455	0.1772	0.0742
	(0.081)	(0.075)	(0.078)	(0.079)	(0.079)	(0.082)	(0.079)	(0.083)	(0.073)	(0.073)	(0.071)	(0.069)	(0.08)	(0.077)

Table B1: Estimated coefficients of the auxiliary regression specified by equation (8) with different sets of controls in the country-specific regression specified by equation (1).

Table B2: Results of OLS Estimation of equation (2)

R-squared	0.227				N	68
Mean Firm Size	Coefficient	Std. err.	t	P> $\|t\|$	[0.025	0.975]
Intercept	-22.1524	7.41	-2.989	0.004	-36.947	-7.358
ln GDPpc	3.3508	0.76	4.402	0.0	1.831	4.871

B2.3: Firm Size Dispersion

As was the case for calculating the average firm size, We used a different data source to calculate firm size dispersion. Poschke (2018) merges data from the Global Entrepreneurship Monitor and the Amadeus database to compute several moments to describe the firm size distribution in over 35 countries. We use that data, winsorized, to exclude possible outliers by dropping the top and bottom 2.5% of values, which we merge with our data on GDP per capita, to run the following regression to obtain an OLS line of best fit and point estimates of interquartile range of the firm size distribution at the 4 stages of development:

$$iqr_i = \alpha_1 + \alpha_2 \ln(GDPpc_i) + v_i. \tag{3}$$

We replicate the finding in Poschke (2018), who shows that firm size dispersion is increasing with development. Figure 1 (Panel C) shows the country-level data from Poschke (2018) as well as the fitted line obtained by estimating equation (3) via OLS and the point estimates at the 4 stages of development. Table B3 shows results.

The value for the IQR of firm size in Colombia is imputed using the cross-country regression (3), since it is not available in Poschke (2018),

Table B3: Results of OLS Estimation of equation (3)

R-squared	0.264				N	39
IQR	Coefficient	Std. err.	t	P> $\|t\|$	[0.025	0.975]
Intercept	-8.2774	3.47	-2.383	0.022	-15.315	-1.24
ln GDPpc	1.2252	0.34	3.638	0.001	0.543	1.907

B2.4: Wage Dispersion

For this target, we use the WBES data. The data are again winsorized at the country level by establishment wages to exclude possible outliers. At each country-year pair, we compute the weighted standard deviation of the average wages paid in each establishment. We then merge the resulting dataset with the GDP per capita data and estimate the following regression via OLS:

$$std(\ln(w))_i = \alpha_1 + \alpha_2 \ln(GDPpc_i) + v_i. \tag{4}$$

We find a strong negative relationship between GDP per capita and the dispersion of wages across firms. Figure 1 (Panel D) shows the country-level data, the fitted values from the cross-country regression, and the point estimates at each of the 4 stages of development to be used as targets in the SMM estimation of the model. Table B4 shows results.

Table B4: Results of OLS Estimation of Equation (4)

R-squared	0.273				N	125
Std of Log-Wage	Coefficient	Std. err.	t	P> $\|t\|$	[0.025	0.975]
Intercept	2.1364	0.22	9.866	0.0	1.708	2.565
ln GDPpc	-0.1569	0.02	-6.795	0.0	-0.203	-0.111

B2.5: Number of Firms

Finally, to construct the targeted number of firms, we use the WBES data merged with the GDP per capita data and estimate the following regression via OLS:

$$J_i = \alpha_1 + \alpha_2 \ln(GDPpc_i) + v_i. \tag{5}$$

Figure 1 (Panel A) shows the country-level data, the fitted values from the cross-country regression, and the point estimates at each of the 4 stages of development to be used as targets in the SMM estimation of the model. Table B5 shows results.

Table B5: Results of OLS Estimation of equation (5)

R-squared	0.207				N	112
Number of Firms	Coefficient	Std. err.	t	P> $\lvert t \rvert$	[0.025	0.975]
Intercept	-201.8617	52.21	-3.866	0.0	-305.339	-98.385
ln GDPpc	29.5728	5.52	5.359	0.0	18.637	40.509

B3: WBES Sample Summary

Table B6: Summary statistics for the harmonized WBES sample merged with GDP per capita in 2017 USD in PPP terms. In countries with multiple WBES waves, the reported GDP per capita is an average over the years of each wave.

Country	Total Number of Observations	Survey Waves	GDP per capita (PPP 2017 USD)
Gambia, The	325	2006 2018	2000
Mali	1035	2007 2010 2016	2019
Zimbabwe	600	2016	2287
Solomon Islands	151	2015	2535
Lesotho	150	2016	2688
Nepal	850	2009 2013	2777
Tajikistan	1071	2008 2013 2019	2845
Senegal	1107	2007 2014	2847
Benin	150	2016	2859
Zambia	1805	2007 2013 2019	3115
Cameroon	724	2009 2016	3483
Djibouti	266	2013	3664
Cambodia	373	2016	3762
Papua New Guinea	65	2015	3813
Myanmar	1239	2014 2016	3884
Ghana	1214	2007 2013	3925

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Table B6: Summary statistics for the harmonized WBES sample merged with GDP per capita in 2017 USD in PPP terms. In countries with multiple WBES waves, the reported GDP per capita is an average over the years of each wave.

Country	Total Number of Observations	Survey Waves	GDP per capita (PPP 2017 USD)
Bangladesh	2440	2013 2022	3933
Kenya	2439	2007 2013 2018	4020
Timor-Leste	364	2021 2015	4131
Pakistan	1247	2013	4267
Kyrgyz Republic	865	2009 2013 2019	4700
Sudan	662	2014	4777
Nigeria	4567	2007 2014	4828
Honduras	1128	2006 2010 2016	4914
Nicaragua	1147	2006 2010 2016	4916
India	18657	2022 2014	5071
Mauritania	387	2006 2014	5149
Uzbekistan	1995	2008 2013 2019	5862
Lao PDR	1330	2009 2012 2016 2018	6079
West Bank and Gaza	799	2013 2019	6182
Philippines	2661	2009 2015	6405
Bolivia	1339	2006 2010 2017	6858
Vietnam	2049	2009 2015	7049
Angola	785	2006 2010	7170
Morocco	1503	2013 2019	7285
Eswatini	457	2006 2016	7376
Guatemala	1457	2006 2010 2017	7544
El Salvador	1772	2006 2010 2016	7695
Iraq	1775	2011 2022	8493
Indonesia	2764	2009 2015	8975

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Table B6: Summary statistics for the harmonized WBES sample merged with GDP per capita in 2017 USD in PPP terms. In countries with multiple WBES waves, the reported GDP per capita is an average over the years of each wave.

Country	Total Number of Observations	Survey Waves	GDP per capita (PPP 2017 USD)
Belize	150	2010	8989
Kosovo	743	2013 2009 2019	9044
Namibia	909	2006 2014	9464
Jamaica	376	2010	9700
Guyana	165	2010	9832
Bhutan	253	2015	9877
Mongolia	1082	2009 2013 2019	10042
Peru	2635	2006 2010 2017	10126
Sri Lanka	610	2011	10190
Moldova	1083	2009 2013 2019	10272
Tunisia	1207	2013 2020	10306
China	2700	2012	10371
Egypt, Arab Rep.	7786	2013 2016 2020	10447
Jordan	1174	2013 2019	10547
Ecuador	1385	2006 2010 2017	10609
Armenia	1280	2009 2013 2020	10952
Albania	1041	2013 2007 2019	11388
Paraguay	1338	2006 2010 2017	11446
St. Vincent and the Grenadines	154	2010	11606
Georgia	1314	2008 2013 2019	12029
Bosnia and Herzegovina	1083	2009 2013 2019	12159
Colombia	2935	2006 2010 2017	12306
Dominica	150	2010	12335

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Table B6: Summary statistics for the harmonized WBES sample merged with GDP per capita in 2017 USD in PPP terms. In countries with multiple WBES waves, the reported GDP per capita is an average over the years of each wave.

Country	Total Number of Observations	Survey Waves	GDP per capita (PPP 2017 USD)
Grenada	153	2010	12494
Botswana	610	2006 2010	12970
South Africa	2034	2007 2020	13071
Ukraine	3190	2008 2013 2019	13182
Brazil	1802	2009	13917
Azerbaijan	995	2009 2013 2019	14220
Dominican Republic	719	2010 2016	14322
St. Lucia	150	2010	14448
North Macedonia	1086	2009 2013 2019	14662
Serbia	1109	2009 2013 2019	16018
Barbados	150	2010	16020
Thailand	1000	2016	16393
Mauritius	398	2009	16625
Costa Rica	538	2010	16667
Lebanon	1093	2013 2019	17676
Belarus	1233	2008 2013 2018	17908
Mexico	2960	2006 2010	18236
Suriname	385	2018 2010	18347
Montenegro	416	2009 2019 2013	18421
Antigua and Barbuda	151	2010	18702
Uruguay	1575	2006 2010 2017	19214
Bulgaria	2368	2007 2009 2013 2019	19259
Panama	969	2006 2010	19483
Chile	2050	2006 2010	20282

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Table B6: Summary statistics for the harmonized WBES sample merged with GDP per capita in 2017 USD in PPP terms. In countries with multiple WBES waves, the reported GDP per capita is an average over the years of each wave.

Country	Total Number of Observations	Survey Waves	GDP per capita (PPP 2017 USD)
Argentina	3108	2006 2010 2017	22599
Kazakhstan	2590	2009 2013 2019	23229
Romania	1895	2009 2013 2019	24405
St. Kitts and Nevis	150	2010	24573
Russian Federation	6547	2012 2009 2019	25376
Latvia	966	2009 2013 2019	25819
Malaysia	2221	2015 2019	25913
Croatia	1397	2007 2013 2019	26557
Poland	2366	2009 2013 2019	27201
Trinidad and Tobago	370	2010	27329
Hungary	1406	2013 2009 2019	27383
Slovak Republic	972	2009 2013 2019	27533
Greece	600	2018	29141
Lithuania	904	2009 2013 2019	29613
Estonia	906	2009 2013 2019	30339
Bahamas, The	150	2010	34688
Slovenia	955	2009 2013 2019	34773
Portugal	1062	2019	34946
Israel	483	2013	36436
Spain	1051	2021	37913
Cyprus	240	2019	41739
Italy	760	2019	42739
France	1566	2021	44993
Malta	242	2019	45426
Finland	759	2020	47444

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Table B6: Summary statistics for the harmonized WBES sample merged with GDP per capita in 2017 USD in PPP terms. In countries with multiple WBES waves, the reported GDP per capita is an average over the years of each wave.

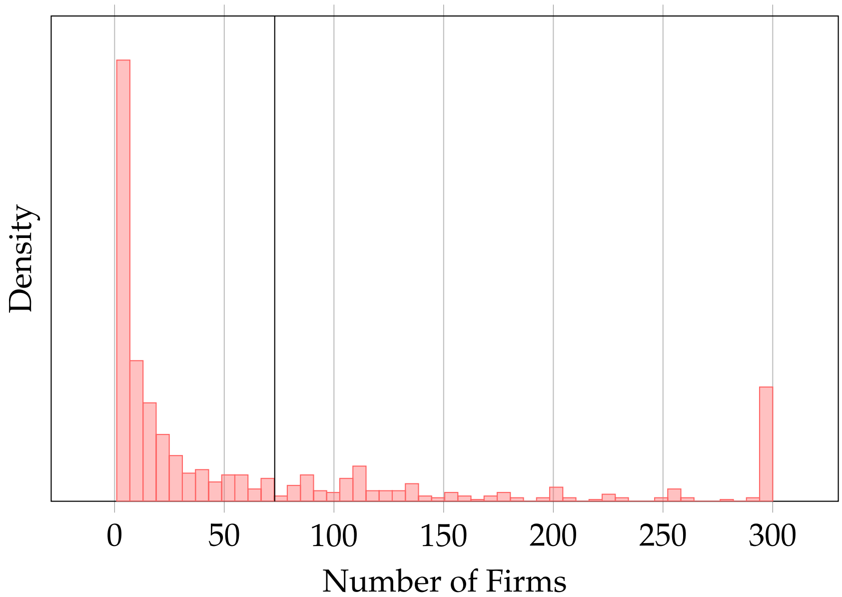
Country	Total Number of Observations	Survey Waves	GDP per capita (PPP 2017 USD)
Belgium	614	2020	48979
Sweden	1191	2014 2020	50295
Germany	1694	2021	53180
Austria	600	2021	54121
Netherlands	808	2020	54275
Denmark	995	2020	55519
Ireland	606	2020	91100
Luxembourg	170	2020	111751

Estimation Appendix

C1: Distribution of Number of Firms

Figure C.1 reports the distribution of firms across different local labor markets in Colombia. While the average number of firms is 73, there is significant variation: while many local labor markets feature only a handful of firms, a substantial fraction of them is populated by more than 300 companies. In the estimation, we use the average number of firms across local labor markets as a target to identify the entry cost.

Figure C.1: Number of Firms by Local Labor Market in Colombia

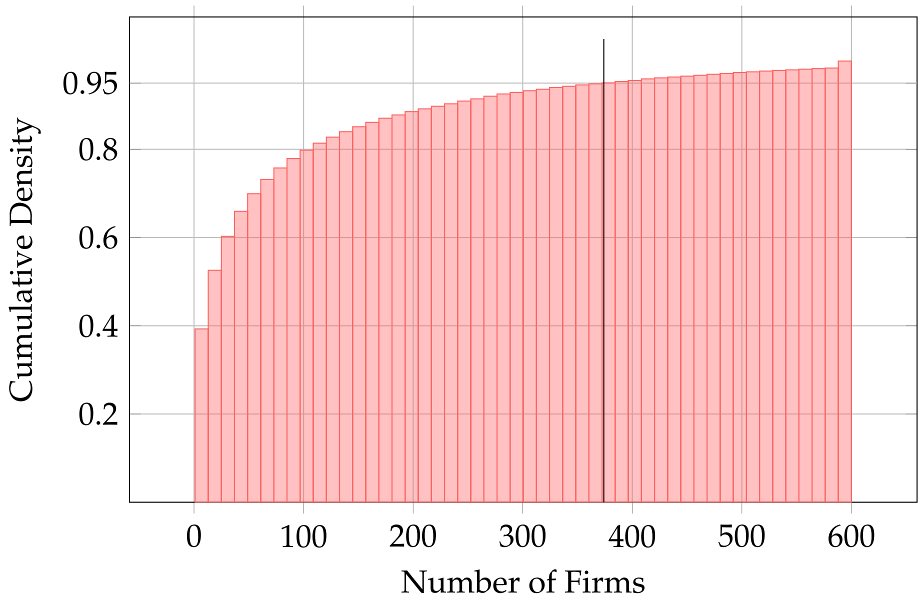


Notes: Distribution of the number of firms in region-sector tuples in Colombia. The vertical black line represents the average, used as a target.

While the average number of firms is lower, the distribution looks very similar to the one documented for the US by Berger et al. (2022).

We fix the number of potential entrants, $\bar{E}$, ex-ante, letting it be large enough to cover 95% of the observed distribution of the number of firms in a given country-year-region-industry cell in the WBES dataset. Figure C.2 shows the histogram of the number of firms at each cell.

Figure C.2: Number of Firms by Labor Market



Notes: Cumulative distribution of the number of firms in country-region-sector triplets in the WBES data. The vertical black line represents the fixed number of potential entrant firms in the model, $\bar{E}$, which covers over 95% of observed markets.

C2: Targeted Moments

Table C1 reports the targeted moments for each synthetic country and Colombia.

Table C1: Targeted Moments

log GDP per capita	Mean Firm Size	Firm Size Dispersion	Wage Dispersion	Firm Size Wage Premium	Number of Firms
8 ($2,980)	4.654	1.524	0.881	0.068	35
9 ($8,100)	8.005	2.749	0.724	0.058	64
10 ($22,000)	11.356	3.975	0.567	0.047	94
11 ($59,900)	14.707	5.2	0.411	0.036	123
Colombia ($12,300)	8.814	3.261	0.669	0.069	73

Notes: The table shows the targeted moments for each country in the estimation.

The loss function used in the estimation is the sum of squared percentage deviations

$$l = g(\omega)'\mathbb{I}g(\omega), \tag{6}$$

where

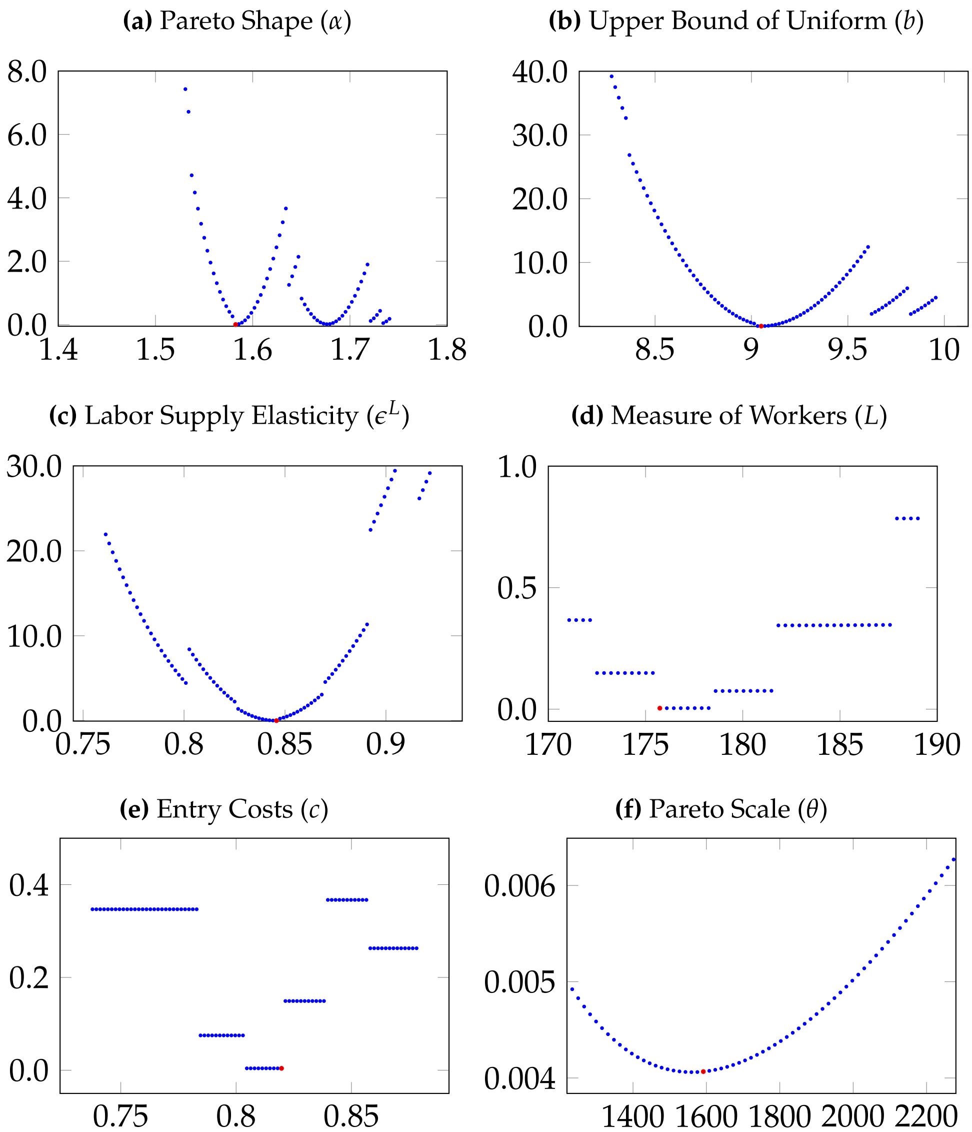
$$g(\omega) = \left[1 - \frac{\gamma^s(\omega)}{\gamma^d}\right],$$

is a vector of percentage deviations of the simulated moments, $\gamma^s(\omega)$ from the observed (targeted) ones, γ^d. The standard errors are calculated using the Delta method.

C3: Global Minima in Estimation

To illustrate the identification of the model parameters, we conduct the following exercise. For each parameter ($\alpha, b, \epsilon^L, L, c, \theta$), we plot the loss function around the estimate for a country with log GDP per capita of 9. Figure C.3 shows the results. Despite the discontinuous nature of the objective function that we minimize, our estimates appear to be on a well-defined global minimum.

Figure C.3: Global Minima in Estimation



Notes: Each of the 6 panels shows the loss function evaluated at the estimated parameter vector, changing only the parameter in each subtitle. The red dot shows the estimated parameter value. The dashed line goes through the minimum value of the loss function found.

C4: Model Fit

In Table C2, we report the estimated parameters from estimating equations (1), (2), (3), (4) and (5) on the data and on the model's simulated moments. As in Figure 2, the table shows a very close fit for the firm size wage premium, the average firm size, firm size dispersion, the wage dispersion, and number of firms.

Table C2: Auxiliary regressions with observed and simulated data

	Data		Model	
	Intercept	Slope	Intercept	Slope
Regression				
Firm Size Wage Premium	0.155	-0.011	0.156	-0.011
Average Firm Size	-22.152	3.351	-19.799	3.046
Firm Size Dispersion	-8.277	1.225	-8.928	1.309
Wage Dispersion	2.136	-0.157	2.187	-0.164
Number of Firms	-201.862	29.573	-201.846	29.753

Notes: This table reports data and model-based estimates of equations (1), (2), (3), (4) and (5) using both the data and model.

C5: Endogenous Entry

Table C3 reports the estimated parameters for Colombia obtained without targeting the number of firms in the economy and setting the entry cost to zero.

Table C3: Estimates with zero entry cost: Colombia.

LS Elasticity (ϵ^L)	Mass of Workers (L)	Pareto Shape (α)	Pareto Scale (θ)	Uniform Dispersion (b)	Entry Cost (c_e)
8.70	962.85	1.50	7046.08	24.66	0.00
(0.118)	(7.689)	(0.001)	(0.217)	(0.849)	(0.0)

Notes: This table reports the estimate of the labor supply elasticity ϵ^L, measure of workers, L, Pareto shape, α, Pareto scale, θ, dispersion of amenities, b, and entry cost c_e, for Colombia, for the case without entry costs and without targeting of the number of firms.

Table C4 shows data targets (row A) and simulated moments obtained by estimating the model with a zero entry cost (row B).

Table C4: Model fit with zero entry cost: Colombia

Scenario	log GDPpc	Mean Firm Size	Firm Size Dispersion	Wage Dispersion	Firm Size Wage Premium	Number of Firms
A. Data	9.418	8.814	3.261	0.669	0.069	73
B. Zero Entry Cost	9.419	7.703	3.751	0.596	0.070	125

Notes: The table shows the simulated moments for Colombia in the baseline estimation and the estimation without entry costs. Row A refers to the empirical targets. Row B refers to the simulated statistic obtained with a model with zero entry cost.

C6: Distribution of Amenities

In the main estimation, we assume that firms' amenities follow a uniform distribution with bounds 0 and b. In this section of the Appendix, we show that our estimates are robust to different functional form assumptions. As the Gamma distribution has two parameters, we use two moments of wage distribution as targets: dispersion (interquartile range) and skewness of the residual wage distribution. In particular, we re-estimate the model for Colombia, assuming that the amenities of firms follow a Gamma with scale and shape parameters a and b. Table C5 reports the estimated parameters with the Gamma distribution, which is quite flexible and can take different forms depending on a and b, together with the baseline estimates where amenities are distributed uniformly.

Table C5: Estimates with Gamma distribution for amenities: Colombia.

	LS Elasticity (ϵ^L)	Mass of Workers (L)	Pareto Shape (α)	Pareto Scale (θ)	Upper Bound Uniform (b)	Gamma Shape (a)	Gamma Scale (b)	Entry Cost (c_e)
A. Uniform	2.295	675.105	1.685	8669.776	6.486	-	-	1.247
	(0.353)	(16.871)	(0.001)	(0.182)	(0.466)	-	-	(0.0)
B. Gamma	2.424	559.113	1.609	6718.269	-	2.029	0.971	0.422
	(0.866)	(28.552)	(0.001)	(0.202)	-	(1.641)	(1.942)	(0.0)

Notes: This table reports robustness estimates of the labor supply elasticity ϵ^L, measure of workers, L, Pareto shape, α, Pareto scale, θ, upper bound of the uniform distirbution of amenities, b, shape and scale of the Gamma distribution of amenities, a and b, and entry cost c_e, for Colombia. The entry cost is reported as a fraction of the Pareto scale, θ.

In the robustness estimation, we estimate the shape and scale of the Gamma distribution to be 2.265 and 1.036, respectively. Compared to the baseline, this implies a lower average value for amenities (2.35 against 3.56) and a lower dispersion (1.56 against 2.06). Nevertheless, moving from a uniform to a Gamma distribution does not alter our estimate of the labor supply elasticity (2.41 against 2.43). Table C6 shows empirical targets (row A) and the simulated moments obtained using a model with Gamma distribution for amenities (row B).

Table C6: Model fit with Gamma distribution for amenities: Colombia

	log GDPpc	Mean Size	Firm	Firm Size Dispersion	Log-Wage Skewness	Wage Dispersion	Firm Size Wage Premium	Number of Firms
A. Data	9.418	8.814		3.261	-0.270	0.669	0.069	73
B. Uniform	9.419	8.883		3.459	-	0.634	0.070	76
C. Gamma	9.483	6.989		3.274	-0.269	0.717	0.069	80

Notes: The table shows the simulated moments for Colombia with a Gamma distribution of amenities. Row A refers to the empirical targets. Row B refers to the simulated statistic obtained with a model with Gamma distribution for amenities.

C7: Estimation Using WBES Firm Size Distributions

In the baseline estimation, we use data from Bento and Restuccia (2017) and Poschke (2018) because these data sources provide better coverage for high-income countries. In this Appendix, we show the parameter estimates when all targeted moments are constructed using the WBES.

Table C7: Targeted Moments from WBES

log GDP per capita	Mean Firm Size	Firm Size Dispersion	Wage Dispersion	Firm Size Wage Premium	Number of Firms
8 ($2,980)	7.804	1.938	0.881	0.068	35
9 ($8,100)	8.354	2.002	0.724	0.058	64
10 ($22,000)	8.904	2.066	0.567	0.047	94
11 ($59,900)	9.453	2.13	0.411	0.036	123
Colombia ($12,300)	10.927	2.205	0.669	0.069	73

Notes: The table shows the targeted moments for each country in the estimation.

Table C8: Simulated Moments

log GDPpc	Mean Firm Size	Firm Size Dispersion	Wage Dispersion	Firm Size Wage Premium	Number of Firms
8 ($2,980)	6.513	1.960	0.839	0.069	35
9 ($8,100)	7.394	2.298	0.619	0.058	70
10 ($22,000)	7.577	2.204	0.468	0.046	97
11 ($59,900)	8.098	2.322	0.346	0.036	115
Colombia ($12,300)	8.186	2.582	0.532	0.070	73

Notes: The table shows the simulated moments for each country in the estimation.

The WBES dataset surveys establishments with more than 5 employees. As a result, for each country in the sample, we impute the missing support for firm size distribution by fitting a Pareto distribution to the observed firm size (number of full-time employees) data. We first estimate the shape parameter for a scale parameter of 5 employees. Then, we use the estimated shape parameters to obtain a value for the average firm size and size dispersion (interquartile range), imposing a scale parameter equal to 1 employee. Table C7 reports the resulting targets for average firm size and size dispersion. Table C8 reports the

Table C9: Estimated model parameters.

log GDP per capita	LS Elasticity (ϵ^L)	Mass of Workers (L)	Pareto Shape (α)	Pareto Scale (θ)	Uniform Dispersion (b)	Entry Cost (c_e)
8 ($2,980)	0.97	227.95	1.58	1501.07	9.6	1.08
	(0.567)	(56.191)	(0.004)	(0.25)	(0.878)	(0.0)
9 ($8,100)	1.39	517.56	1.9	7540.64	4.56	1.37
	(0.419)	(32.804)	(0.002)	(0.149)	(1.304)	(0.0)
10 ($22,000)	1.93	734.97	2.39	34480.16	4.17	1.12
	(0.333)	(25.148)	(0.001)	(0.078)	(2.155)	(0.0)
11 ($59,900)	3.16	931.32	2.89	144024.74	4.76	1.09
	(0.253)	(17.425)	(0.001)	(0.05)	(0.365)	(0.0)
Colombia ($12,300)	2.19	597.59	2.14	15366.88	6.03	1.17
	(0.293)	(16.82)	(0.001)	(0.107)	(0.243)	(0.0)

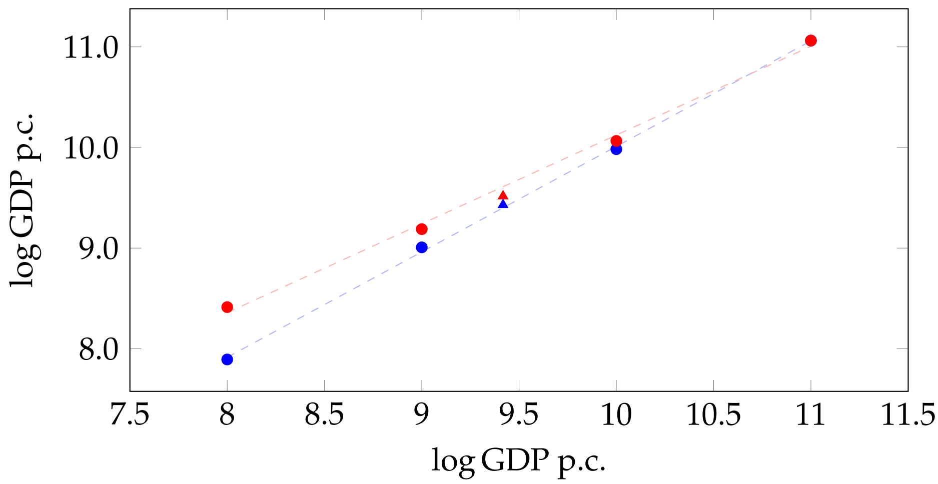
Notes: This table reports the estimate of the labor supply elasticity ϵ^L, measure of workers, L, Pareto shape, α, Pareto scale, θ, dispersion of amenities, b, and entry cost c_e, for 4 synthetic targeted countries. The entry cost is reported as a fraction of the Pareto scale, θ. Standard errors in parenthesis are computed using the Delta method.

model-based simulated moments.

Table C9 reports the parameter values estimated using WBES targets for average firm size and firm size dispersion.

Figure C.4: Counterfactual Results (WBES)

(a) GDP per capita



Notes: Blue dots show the baseline (log) GDP per capita, and red dots show the counterfactual (log) GDP per capita. Baseline and counterfactual moments for Colombia are represented by triangles.

Compared to our baseline estimates in Table 1 of the main text, the estimates for the labor supply elasticity are largely unchanged. For the poorest country, we estimate a value of 0.97 against 0.85. For the richest country, we estimate a value of 3.16 against 3.06. The estimates of labor supply elasticity are still increasing with GDP per capita, suggesting the identification is robust to alternative targets for the average firm size and the size dispersion.

Using the estimates in Table C9 we also perform the same counterfactual exercise as in the main text. Keeping all the parameters constant, we increase the labor supply elasticity of each country to the value of the richest one. Figure C.4 reports baseline and counterfactual (log) GDP per capita across countries when parameters are estimated using moments from the WBES. The gains in GDP per capita are remarkably similar to those reported in the main text: the poorest countries, such as Zambia or Senegal, would see an increase in their GDP per capita of up to 52 percent if they had the same labor supply elasticity as countries at the top of the development ladder, such as the Netherlands or Denmark. The increase in GDP per capita for middle-income countries, such as Indonesia or Peru, would be approximately 18 percent. For Colombia, the increase in GDP per capita would be around 8 percent.

D. Counterfactual Appendix

D1: Further Counterfactual Results

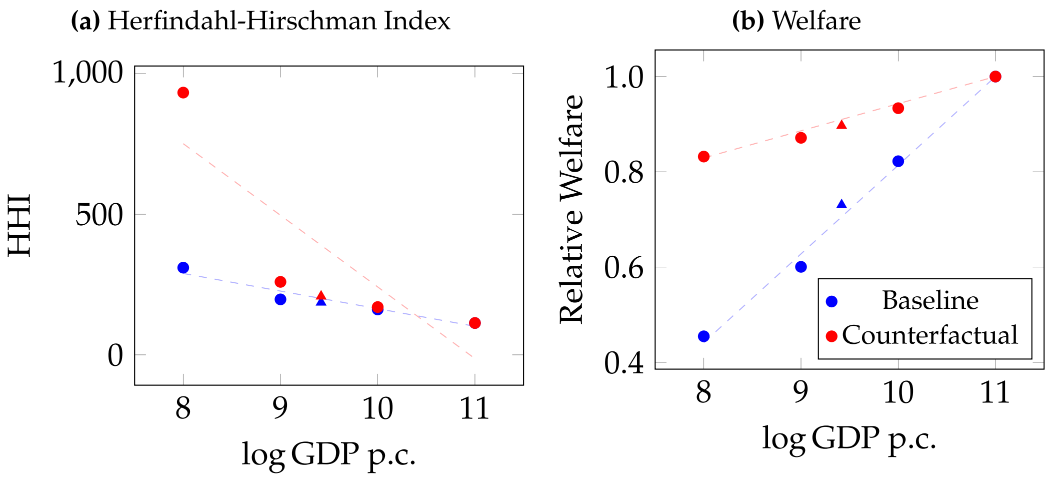
Figure D.1 reports how concentration, measured by the Herfindahl-Hirschman index (Panel A) and a measure of model-based welfare (Panel B) changes with development in the baseline and counterfactual. Welfare is computed as the expected worker-level utility, i.e.,

$$W = \ln\left(\sum_{j=1}^{J} \exp(\epsilon^L \ln(w_j) + a_j)\right)$$

and it is expressed relative to the value of the richest country.

Concentration declines over development, while model-based welfare is steeply increasing. A counterfactual increase in the elasticity of labor supply leads to a higher concentration and welfare, particularly in the poorest targeted countries.

Figure D.1: Further Counterfactual Results



Notes: Blue dots show simulated moments at the baseline, red dots show simulated moments under the counterfactual. Baseline and counterfactual moments for Colombia are represented by triangles. Welfare is normalized with respect to the richest country.

Tables D1 and D2 report a series of outcomes for each targeted country under the baseline equilibrium (column 1), a counterfactual equilibrium obtained by replacing the country-specific labor supply elasticity to the highest estimated value (column 2), and the same counterfactual when the number of firms is fixed at the baseline values (column 3).

Table D1: Counterfactual outcomes

Countries	Baseline	Counterfactual General Equilibrium	Counterfactual Fixed Number of Firms	Explained, %
	(1)	(2)	(3)	(4)
		A. GDP per capita		
8 ($2,900)	1	1.438	1.337	23.066
9 ($8,100)	1	1.169	1.147	13.299
10 ($22,000)	1	1.035	1.033	5.240
11 ($59,000)	1	1.000	1.000	-
Colombia ($12,300)	1	1.049	1.044	9.676
		B. Wage Dispersion		
8 ($2,900)	0.874	0.488	0.435	-13.864
9 ($8,100)	0.687	0.511	0.511	-0.150
10 ($22,000)	0.550	0.469	0.471	2.741
11 ($59,000)	0.404	0.404	0.404	-
Colombia ($12,300)	0.615	0.521	0.526	5.557
		C. Firm Size Dispersion		
8 ($2,900)	0.313	0.507	0.667	-82.740
9 ($8,100)	0.417	0.466	0.474	-17.284
10 ($22,000)	0.475	0.494	0.493	6.003
11 ($59,000)	0.464	0.464	0.464	-
Colombia ($12,300)	0.459	0.476	0.475	2.291
		D. Conditional Firm Size Wage Premium		
8 ($2,900)	1.189	0.314	0.314	-
9 ($8,100)	0.574	0.314	0.314	-
10 ($22,000)	0.383	0.314	0.314	-
11 ($59,000)	0.314	0.314	0.314	-
Colombia ($12,300)	0.403	0.314	0.314	-

Notes: This table reports selected outcomes in the baseline equilibrium (column 1), in a full counterfactual equilibrium (column 2), and in a counterfactual equilibrium with a fixed number of firms (column 3). Column (4) reports the percent change in each outcome explained by changes in the equilibrium number of firms.

Column 4 in both tables reports the percentage change of each outcome explained by counterfactual changes in the number of firms.

Table D2: Counterfactual outcomes

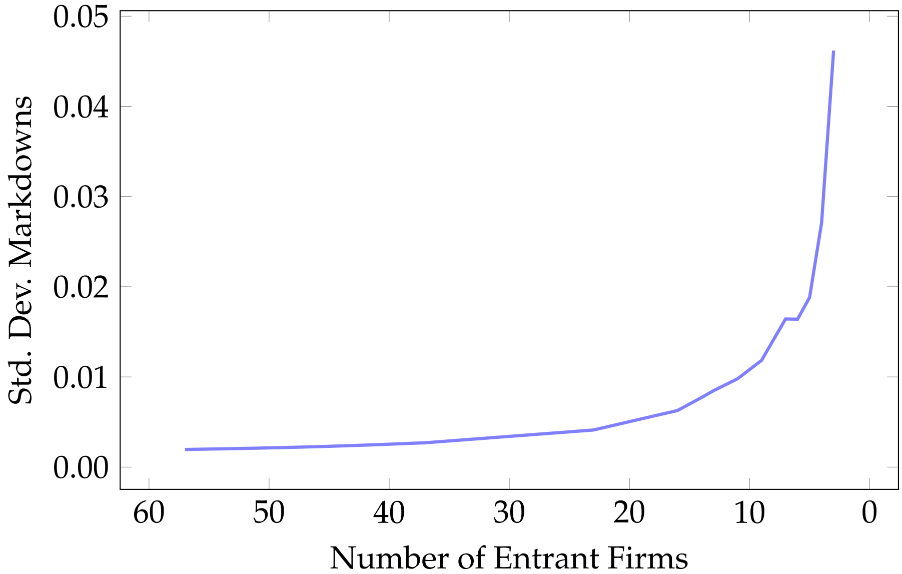
Countries	Baseline (1)	Counterfactual: General Equilibrium (2)	Counterfactual: Fixed Number of Firms (3)	Explained, % (4)
		A. Number of firms		
8 ($2,900)	37	13	37	-
9 ($8,100)	67	56	67	-
10 ($22,000)	93	92	93	-
11 ($59,000)	128	128	128	-
Colombia ($12,300)	74	72	74	-
		B. HH Index		
8 ($2,900)	308.13	983.37	459.03	77.65
9 ($8,100)	197.10	261.65	224.31	57.85
10 ($22,000)	162.66	172.58	170.81	17.89
11 ($59,000)	117.19	117.19	117.19	-
Colombia ($12,300)	195.67	211.39	206.26	32.59
		C. Average Wage		
8 ($2,900)	1	1.648	1.841	-29.928
9 ($8,100)	1	1.337	1.375	-11.516
10 ($22,000)	1	1.112	1.107	3.976
11 ($59,000)	1	1.000	0.996	-
Colombia ($12,300)	1	1.134	1.130	2.992
		D. Welfare		
8 ($2,900)	16.89	31.88	33.76	-12.56
9 ($8,100)	22.62	33.89	34.25	-3.24
10 ($22,000)	31.26	36.38	36.39	-0.12
11 ($59,000)	39.09	39.09	39.08	-
Colombia ($12,300)	29.16	35.01	35.05	-0.66

Notes: This table reports selected outcomes in the baseline equilibrium (column 1), in a full counterfactual equilibrium (column 2), and in a counterfactual equilibrium with a fixed number of firms (column 3). Column (4) reports the percent change in each outcome explained by changes in the equilibrium number of firms.

D2: Strategic Interaction

Figure D.2 reports the standard deviation of markdowns across firms for counterfactual economies that differ in the number of firms. The parameters used to solve the model are those associated with the poorest artificial country. A different number of firms is obtained as an equilibrium outcome by changing the entry cost.

Figure D.2: Markdown Dispersion vs. Number of Firms



Notes: The figure shows the dispersion of markdowns across firms as a function of the number of entrant firms. The parameters used are those of the lowest GDP per capita artificial country, changing only the entry costs to go from a high number of firms to a low number of firms.

Markdowns have a higher dispersion when the number of firms is low and strategic interaction among them is strong. On the other hand, when evaluated at the targeted number of firms (i.e., 37), strategic interaction is likely to play a limited role, as the dispersion in markdown is lower than 1 percent.

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