The Effects of Tax Enforcement on Average Firm Size and Aggregate Productivity

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Abstract

How does tax enforcement affect average firm size and total factor productivity (TFP)? To answer this question, I develop a quantitative model with informality where informal entrepreneurs do not pay taxes but face a probability of detection increasing in firm size. Stricter tax enforcement results in lower informality and affects average firm size and TFP through two mechanisms: as tax enforcement becomes stricter, fewer relatively unproductive agents choose to be entrepreneurs, and fewer entrepreneurs choose to operate in the informal sector. I calibrate the model using Brazilian data. A counterfactual tax enforcement reducing the informality rate by 6 percentage points accounts for 9% and 28% of the observed differences in TFP and average firm size between Brazil and a weighted average of the six largest other Latin American economies.

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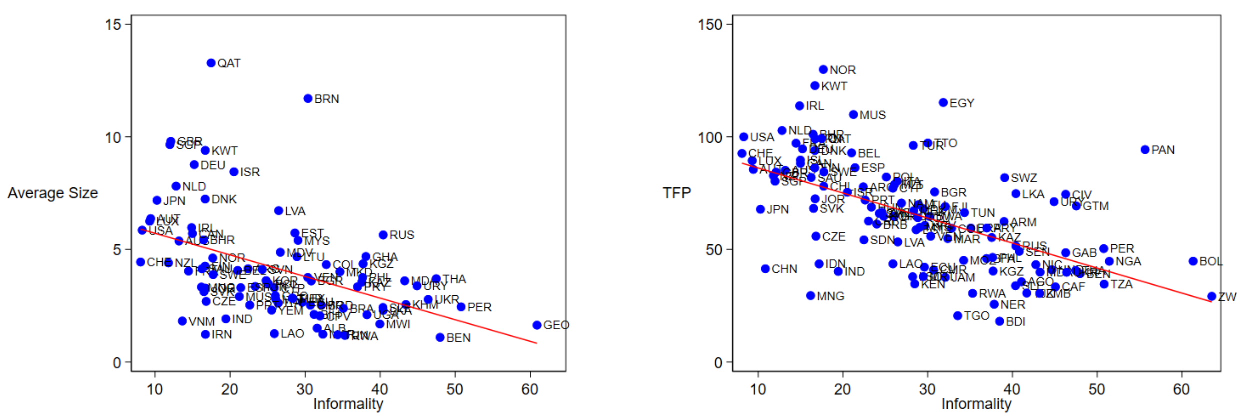
I Introduction

Developing countries are characterized by the presence of a firm size distribution that is highly concentrated on businesses with a low number of employees. In fact, an overwhelming majority of firms and a relatively large fraction of value added are accounted for by micro firms with at most 5 employees.[1] Informality rates among small firms are substantial, reflecting the government's inability to detect and tax these entities. For instance, the informality rate among firms smaller than 5 employees is 84% in Brazil and 94% in Mexico (Alvarez and Ruane (2024)) [2]. In addition, compared to advanced economies, developing countries display lower measures of total factor productivity (TFP), which is generally deemed as the main source of cross-country differences in per-capita income. Figure 1 shows cross-country correlations between informality rates, average firm size (panel a), and TFP (panel b). To sum up, developing countries display coexisting high informality and tax evasion rates, low average firm size, and low aggregate productivity.

Figure 1: Correlation between Informality, Average Firm Size, and TFP across Countries.

(a) Informality and Average Firm Size.

(b) Informality and TFP.



Source: Elgin et al. (2021) for informality, Bento and Restuccia (2021) for average size, Feenstra, Inklaar, and Timmer (2015) for TFP. Informality and TFP data are country averages over the period 2005-2015.

1. Whenever the number of employees is mentioned in this paper, it includes the owner.
2. Data for Brazil are presented in Section III.A.

How much does tax enforcement account for the observed differences in size and productivity across countries? This paper investigates the impact of tax enforcement on average firm size and TFP. To assess the magnitude of the impact, I build a dynamic quantitative model characterized by heterogeneous agents, occupational choice, and the presence of an informal sector. Agents can choose whether to be workers, entrepreneurs in the formal sector, or entrepreneurs in the informal sector. Formal entrepreneurs pay sales and payroll taxes, while informal entrepreneurs do not. However, the latter are detected with a probability that increases with the size of their business. In case of detection, informal entrepreneurs pay the due amount of taxes plus a proportional fine. Tax enforcement is then summarized by the combination of tax rates, penalty rates, and a probability of detection that is an increasing function of the number of employees in the business.

In the model, stricter tax enforcement affects average firm size and TFP through two mechanisms. First, the profitability of operating in the informal sector declines, inducing some relatively unproductive agents to be workers. These agents would operate as informal entrepreneurs with looser tax enforcement because they would be able to circumvent tax payments. Moreover, these entrepreneurs would operate at a low scale, given the positive relationship between productivity and size. Consequently, average size and productivity increase thanks to a composition effect, referred to as the *selection channel*. Second, to avoid detection by the tax authority, informal entrepreneurs operate at a lower scale compared to formal entrepreneurs of the same productivity. Therefore, as the rate of informality decreases due to stricter tax enforcement, fewer entrepreneurs decide to keep their scale at suboptimally low levels. This *detection channel* has a positive effect on average firm size and allocative efficiency.

To calibrate the model, I use data from Brazil. More specifically, I substantially rely on the *Economia Informal Urbana* (ECINF), a detailed firm-level survey lastly conducted in 2003, which contains information on informality status and number of employees. The calibrated model successfully replicates several features of the Brazilian economy, such as the high share of micro and small firms, high informality (36% of GDP) and tax evasion rates, high entrepreneurship and self-employment rates, and the observation that formal entrepreneurs are, on average, larger in size and more productive than informal entrepreneurs.

I then perform a counterfactual analysis to measure the impact of tax enforcement. To simulate stricter tax enforcement in Brazil, I change the parametrization of the detection probability function to match an informality rate of 30%, which is the GDP-weighted average of the six largest Latin American economies in 2003. The counterfactual calibrated economy generates an increase in output and TFP by approximately 4.3% and 0.5%, respectively, and a rise in average firm size from 2.08 in the baseline to 2.37. These changes account for about 13%, 9%, and 28% of the observed differences in GDP per capita, TFP, and average firm size between Brazil and the weighted averages of the countries in the group. These results are consistent across several exercises in which different countries or groups of countries are taken as counterfactuals. Overall, tax enforcement can account for about 25-30% of the estimated differences in average firm size and for about 8-15% of the estimated differences in GDP per capita and TFP.

What are the mechanisms through which stricter tax enforcement results in higher TFP and average firm size? The counterfactual economy displays a lower rate of entrepreneurship (3 percentage points lower than in the baseline) and lower rates of informality for given values of firm-level productivity. Overall, there is a reallocation of resources from low-productivity informal entrepreneurs to high-productivity formal entrepreneurs. From a quantitative point of view, decomposing the impact between the selection and detection channel highlights that both channels have substantial positive impacts on average firm size (they both account for about 50% of the overall impact), while only the detection channel has a significant positive effect on TFP.

This paper proceeds as follows. Section II introduces the quantitative model. Section III presents the data and the baseline calibration of the model. Section IV describes the counterfactual experiments and presents the quantitative results. Section V concludes.

Related literature. This paper relates to three main strands of literature. First, it relates to the literature studying the aggregate effects of tax enforcement, either in developing countries or in advanced economies (For example, Bigio and Zilberman (2011); Bachas, Fattal Jaef, and Jensen (2019)). My framework shows some similarities with the work of

Leal Ordóñez (2014), who focuses on Mexico, and Di Nola et al. (2021), who focus on the US, for the presence of selection and detection channels as the main mechanisms affecting aggregate outcomes. With regard to cross-country studies, Bachas, Fattal Jaef, and Jensen (2019) analyze how size-dependent taxation affects TFP across several countries and sectors. Differently from this paper, which relies on informal businesses' statistics for the quantification, Bachas, Fattal Jaef, and Jensen (2019) use World Bank data from registered formal firms to estimate the model and perform counterfactual analysis.

The paper is also related to the literature that analyzes the relationship between informality and aggregate outcomes. These studies often focus on a single country such as Brazil (Ulyssea (2018); Erosa, Fuster, and Martinez (2023)) or Mexico (Leal Ordóñez (2014)). Ulyssea (2018) studies the effects of policy reforms reducing informality on output, TFP, and welfare. The author develops a quantitative model that features two margins of informality: an *extensive margin*, associated with the business side, and an *intensive margin*, which reflects the hiring of "off-the-books" workers by formal firms. He then shows that policies affecting the intensive margin do not necessarily increase output and welfare. Erosa, Fuster, and Martinez (2023) extend Ulyssea's framework to assess the interaction between informality and financial frictions. While getting similar qualitative results as in Ulyssea (2018), they show that tight borrowing constraints amplify the negative effects of informality on the allocation of resources. My work distinguishes from the above papers in three dimensions. First, my model introduces a microfoundation of the relationship between size and the cost of informality that depends on tax enforcement and is disciplined by statutory tax rates and moments from the informal firm size distribution. Second, I focus my analysis on the effects on average firm size and TFP. Third, I estimate how tax enforcement can account for the differences in average firm size and TFP between Brazil and other countries displaying lower informality rates.

Finally, the paper is connected with the literature studying the effects of correlated distortions and size-dependent policies on TFP (Restuccia and Rogerson (2008); Guner, Ventura, and Xu (2008); Hsieh and Klenow (2009); Buera, Moll, and Shin (2013); David and Venkateswaran (2019)) and the firm size distribution (Garicano, Lelarge, and Reenen (2016); Bento and Restuccia (2017); Poschke (2018); Bento and Restuccia (2021); Fattal-Jaef

(2022)). For example, Bento and Restuccia (2021) show how different levels of elasticity between distortions and size can account for cross-country differences in average establishment size. My contribution to this literature is to highlight how tax enforcement could represent one of the underlying sources of the measured differences in correlated distortions across countries and a relevant factor in accounting for differences in aggregate outcomes.

II Model

Time is discrete. I consider a small open economy with fixed interest rate r. The economy is populated by a continuum of infinitely-lived individuals who are heterogeneous in their ability to run a business. Individuals choose whether to be entrepreneurs or workers. Each worker inelastically supplies one unit of labor. Entrepreneurs additionally choose whether to operate the firm in the formal or informal sector.

Entrepreneurs. Both formal and informal entrepreneurs adopt the same technology in producing a homogeneous final good. Entrepreneur i's production function is

$$y_i = z_i \times \underbrace{(k_i^{\alpha}(\bar{\ell} + n_i)^{1-\alpha})^{\gamma}}_{f(k_i,n_i)} - \theta n_i, \tag{1}$$

where y denotes output, z is managerial ability (i.e., firm-level productivity), k is capital, $\bar{\ell}$ is the owner's labor supply entering the production function, and n is hired labor. $\alpha \in (0,1)$ denotes the capital share, while $\gamma \in (0,1)$ denotes the span-of-control parameter. The value of $\bar{\ell}$ is common across entrepreneurs. Entrepreneurial ability z_i evolves over time according to an $AR(1)$ process. Capital is borrowed at a rate $(r+\delta)$, where δ denotes depreciation, while labor is provided by workers at an hourly wage rate w. Entrepreneurs also pay a variable cost proportional to the number of employees $\theta \times n_i$, which reflects the cost of managing employees.[3] The baseline economy is characterized by perfect financial

3. Adding the variable cost $\theta \times n$ helps capture the very high level of self-employment among Brazilian informal firms.

markets, so entrepreneurs can rent any desired amount of capital for production.

Each entrepreneur decides whether to keep the firm formal or informal. Formal firms pay an output (sales) tax $\tau_y z_i f(k_i, n_i)$ and a payroll tax $\tau_n wn$, while informal firms do not. However, informal firms are detected with probability $p(n)$, with $p'(n) > 0$, that is, the detection probability is increasing in the amount of hired labor used for production. A detected firm has to pay a surcharge $(1+\kappa)$ of its due taxes to the government, with $\kappa > 0$. Therefore, tax enforcement is defined by the combination of tax rates τ_y and τ_n, a surcharge rate κ, and a probability of detection function $p(n)$.

Preferences. Agents maximize the stream of per-period utilities and discount the future at rate β:[4]

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t),$$

where c_t denotes consumption and the utility function $u(\cdot)$ satisfies the usual properties.

Government. The government balances the budget in every period. It collects taxes from entrepreneurs in the formal sector and ex-post punishment amounts from entrepreneurs in the informal sector. The collected revenues are used to finance an exogenous amount of public expenditures G, which does not enter the agents' utility function.

Timing. Within each period, timing is the following:

(i) Productivity shocks realize.

(ii) Agents decide whether to be workers, formal, or informal entrepreneurs.

(iii) Capital and labor decisions are made. Production occurs.

(iv) Formal firms pay taxes to the government. Detected informal firms pay the ex-post punishment amount.

4. I remove the i subscripts hereafter for ease of notation.

(v) Individuals make consumption and saving decisions given after-tax (or punishment) earnings.

Recursive Problems. The worker's problem can be written in the following recursive form:

$$V_W(z,a) = \max_{c,a'} \{u(c) + \beta \mathbb{E}_{z'} V(z',a')\} \tag{2}$$
$$s.t. \;\; c + a' \leq w + (1+r)a,$$
$$a' \geq 0.$$

The formal entrepreneur's problem can be written in the following recursive form:

$$V_F(z,a) = \max_{c,a',k,n} \{u(c) + \beta \mathbb{E}_{z'} V(z',a')\} \tag{3}$$
$$s.t. \;\; c + a' \leq \pi_F(z) + (1+r)a,$$
$$\pi_F(z) = (1-\tau_y) z (k^\alpha (\bar{\ell} + n)^{1-\alpha})^\gamma - (r+\delta)k - [w(1+\tau_n) + \theta] n$$
$$a' \geq 0.$$

The informal entrepreneur's value function is

$$V_I(z,a) = \max_{k,n} \{(1-p(n)) V_I^{nd}(z,a,k,n) + p(n) V_I^d(z,a,k,n)\}, \tag{4}$$

where $V_I^d(z,a,k,n)$ and $V_I^{nd}(z,a,k,n)$ denote the value functions of detected and not detected entrepreneurs, respectively.
For $j = \{d, nd\}$, the recursive problem can be written as

$$
\begin{aligned}
V_I^j(z,a,k,n) =& \max_{c,a'} \{u(c) + \beta \mathbb{E}_{z'} V(z',a'))\} \\
s.t.\ \ c + a' \leq& \pi_I^j(z) + (1+r)a, \\
\pi_I^j(z) =& z(k^\alpha(\bar{\ell}+n)^{1-\alpha})^\gamma - (r+\delta)k - (w+\theta)n - \\
& \mathbb{1}_{j=d} \times [(1+\kappa)(\tau_y z(k^\alpha(\bar{\ell}+n)^{1-\alpha})^\gamma + \tau_n wn)], \\
a' \geq& 0.
\end{aligned} \tag{5}
$$

Finally, an agent with productivity z and assets a chooses an occupation according to

$$
V(z,a) = \max\{V_W(z,a), V_I(z,a), V_F(z,a)\}. \tag{6}
$$

Equilibrium. Given an interest rate r, government expenditures G, a government policy $\{\tau_y, \tau_n, \kappa\}$, and a detection probability function $p(\cdot)$, a *stationary competitive equilibrium* is wage w, occupational choices $o(z,a)$, entrepreneurs' capital and labor policy functions $k(z,a)$, $n(z,a)$, consumption and asset allocations for workers, formal entrepreneurs, detected informal entrepreneurs, and undetected informal entrepreneurs $c_W(z,a)$, $c_F(z,a)$, $c_{I,d}(z,a)$, $c_{I,nd}(z,a)$, $a_W(z,a)$, $a_F(z,a)$, $a_{I,d}(z,a)$, $a_{I,nd}(z,a)$, value functions $V(z,a)$, $V_W(z,a)$, $V_F(z,a)$, $V_I(z,a)$, and a distribution $\mu(z,a)$, such that:

- Worker's value function $V_W(z,a)$ and allocations $c_W(z,a)$, $a_W(z,a)$ solve problem (2).
- Formal entrepreneur's value function $V_F(z,a)$ and allocations $c_F(z,a)$, $a_F(z,a)$, $k(z,a)$, $n(z,a)$ solve problem (3).
- Informal entrepreneur's value function $V_I(z,a)$ and allocations $c_{I,d}(z,a)$, $c_{I,nd}(z,a)$, $a_{I,d}(z,a)$, $a_{I,nd}(z,a)$, $k(z,a)$, $n(z,a)$ solve problem (4).
- Occupational choices $o(z,a)$ are consistent with (6).

- The labor market clears:

$$L = \int_{o(z,a)=W} d\mu(z,a) = \int n(z,a) d\mu(z,a).$$

- Government balances its budget:

$$\begin{aligned} G = &\int_{o(z,a)=F} \big(\tau_y z f(k(z,a), n(z,a)) + \tau_n w n(z,a)\big) \times d\mu(z,a) \\ &+ \int_{o(z,a)=I} p(n(z,a)) \times (1+\kappa)\big(\tau_y z f(k(z,a), n(z,a)) + \tau_n w n(z,a)\big) \times d\mu(z,a). \end{aligned}$$

- The current account surplus/deficit is stationary:

$$\begin{aligned} CA = &\int z f(k(z,a), n(z,a)) d\mu(z,a) - \delta K - G - \theta L \\ &- \int_{o(z,a)=W} c_W(z,a) d\mu(z,a) - \int_{o(z,a)=F} c_F(z,a) d\mu(z,a) \\ &- \int_{o(z,a)=I} \Big[c_{I,d}(z,a) p(n(z,a)) + c_{I,nd}(z,a)(1 - p(n(z,a))) \Big] d\mu(z,a). \end{aligned}$$

- The distribution $\mu(z,a)$ is stationary. Given a one-period ahead transition operator $\mathcal{M}$,

$$\mu = \mathcal{M}(\mu).$$

III Calibration

In this section, I first describe the Brazilian data used for the calibration (Section III.A). Then, I introduce the functional forms (Section III.B) and I separate model parameters in two groups: those who are externally set based on conventional or statutory values, and those who are internally calibrated. For the latter, I choose the parametrization that minimizes the distance between model and data moments (Section III.C). Finally, I show how the calibrated model performs along targeted and non-targeted dimensions (Section III.D).

III.A Data

Data for Brazil are collected from different sources. Moments of informal firms are collected from the *Economia Informal Urbana* (ECINF), a representative survey that was lastly conducted in 2003 to collect information on the informal sector in Brazil. The survey contains characteristics of self-employed workers and employers running a non-agricultural business with up to five employees. Owners are classified as informal if they do not possess a tax identification number (*Cadastro Nacional de Pessoa Juridica* (CNPJ)). By matching owners with employees, it is possible to obtain the number of employees for each business. Additional information such as sector and financial variables is also available. The final sample from which I compute informal firm size distribution moments used in the calibration contains about 30,000 firms. While ECINF displays a comprehensive picture of small formal and informal firms, the size threshold of 5 employees makes the sample not representative of the universe of formal firms. Therefore, I integrate ECINF with statistics on formal firms taken from the *Relação Anual de Informações Sociais* (RAIS), an administrative dataset containing number and characteristics of workers as reported by formal employers.[5]

I use data from the 2003 *Pesquisa Nacional por Amostra de Domicílios* (PNAD), a repeated cross-section representative at the national level, to compute the rate of entrepreneurship. Individuals who are either self-employed or employers are classified as entrepreneurs.

Finally, the share of informal output in the Brazilian economy is taken from Elgin et al. (2021), which provides estimates of informality rates for more than 160 countries over the period 1990-2019.[6] The value for Brazil in 2003 is 36%.

Table 1 summarizes the main data. Of particular relevance are the high rate of entrepreneurship (30%), the high share of informal firms (76%), and the fact that 95% of informal firms have at most two employees.

5. I do not have direct access to the RAIS microdata since it is a restricted administrative dataset. However, I can obtain firm size distribution moments from tabular data and from other papers' statistics.

6. These estimates are obtained through national account statistics and the use of a dynamic general equilibrium model, which determines how optimizing households will allocate labor between formal and informal sectors.

Table 1: Data for Brazil in 2003.

Moments	Source	Data
Informality		
Informality/GDP	Elgin et al. (2021)	0.36
Share of informal firms [a]	Erosa, Fuster, and Martinez (2023)	0.76
Entrepreneurship rate	PNAD	0.302
Size distribution (formal) : firms shares		
1-5	RAIS	0.70
6-10	RAIS	0.14
11-20	RAIS	0.08
21-50	RAIS	0.05
Size distribution (informal) : firms shares		
≤ 1	ECINF	0.834
≤ 2	ECINF	0.949
≤ 5	ECINF	0.998

Source: Own calculations based on ECINF and PNAD (2003), tabular data from RAIS.
a. The figure is obtained by merging sample data from ECINF with administrative data from RAIS.

III.B Functional Forms

I set the utility function to be $u(c_t) = log(c_t)$.

Managerial productivity evolves according to the following AR(1) process:

$$log(z_{t+1}) = \rho \, log(z_t) + \nu_{t+1}, \quad \nu \sim N(0, \sigma_\nu^2). \tag{7}$$

Where ρ and σ_ν denote the persistence and the standard deviation of the productivity process.

Regarding the detection probability function, I follow Di Nola et al. (2021) in adopting a logistic function:

$$p(n) = \frac{1}{1 + p_1 exp(-p_2 n)}. \tag{8}$$

The two parameters to be estimated are p_1 and p_2, which control the inflection point and the slope of the detection probability function, respectively.

Occupational taste shocks. To smooth aggregate labor demand and supply functions and ease the convergence to an equilibrium, I introduce individual-level occupational taste shocks which are realized at the same time as productivity shocks.[7] These shocks are (i) distributed according to a Gumbel distribution with scale parameter σ_ϵ, (ii) iid across occupational choices within individuals, and (iii) iid across individuals and across time. I set the parameter σ_ϵ to 0.1.

The occupational choice for an agent with productivity z, assets a, and taste shocks $\epsilon_W, \epsilon_I, \epsilon_F$ is consistent with

$$V(z,a) = \max\{V_W(z,a) + \epsilon_W, V_I(z,a) + \epsilon_I, V_F(z,a) + \epsilon_F\}. \tag{9}$$

Since the shocks are iid and follow a Gumbel distribution with scale parameter σ_ϵ, the (ex-ante) probability of choosing occupation $o \in \{W, I, F\}$ given (z,a) is

$$q(o|z,a) = exp\left(\frac{V_o(z,a)}{\sigma_\epsilon}\right) \Bigg/ \sum_{o' \in \{W,I,F\}} exp\left(\frac{V_{o'}(z,a)}{\sigma_\epsilon}\right). \tag{10}$$

Moreover, the value function $V(z,a)$ is given by the log-sum formula

$$V(z,a) = \sigma_\epsilon \, log\left(\sum_{o' \in \{W,I,F\}} exp\left(\frac{V_{o'}(z,a)}{\sigma_\epsilon}\right)\right). \tag{11}$$

III.C Choice of Parameters

Externally set parameters. Table 2 shows the parameters that are calibrated outside the model. I set the discount factor β to .96, the capital depreciation rate δ to .05, the capital share α to .33, and the span-of-control parameter ν to .9. Tax and surcharge rates are set according to their statutory values. The sales tax τ_y is set to .293, while the payroll tax is set to .375. The output tax includes two VAT federal taxes of 20 and 9 percent, respectively, while the payroll tax includes social security contributions (20 percent), direct payroll tax

7. The sole purpose of introducing these shocks is computational ease, and the main results do not depend on their inclusion.

(9 percent), and severance contributions (8.5 percent). Finally, the surcharge rate κ is set to the regular penalty, which is 75% of the due taxes (as in Franjo, Pouokam, and Turino (2022)).

Table 2: Externally Set Parameters.

Parameter	**Description**	**Value**	**Source**
β	Discount factor	0.96	Standard value
δ	Capital depreciation rate	0.05	Standard value
α	Capital share	0.33	Standard value
γ	Span-of-control	0.9	Standard value
τ_y	Sales tax	29.3%	Statutory rate
τ_n	Payroll tax	37.5%	Statutory rate
κ	Surcharge rate	75%	Statutory rate

Internally calibrated parameters. There are 6 parameters left to be estimated: the persistence and the standard deviation of the productivity shock ρ and σ_ν, the detection probability parameters p_1 and p_2, the entrepreneurial amount of labor entering the production function $\bar{\ell}$, and the variable cost parameter θ. Model parameters are jointly calibrated and chosen to minimize the distance between the following model statistics and their corresponding moments in the data:

1. Informality rate (output): share of output produced by informal entrepreneurs.
2. Informality rate (firms): share of informal firms (out of all firms).
3. Share of informal self-employed (out of informal firms).
4. Share of informal firms with less than 2 employees (out of informal firms).
5. Share of formal firms with less than 5 employees (out of formal firms).
6. Entrepreneurship rate: sum of self-employed and employers (out of the labor force).

It is important to highlight that parameters p_1 and p_2 are mostly informative of the share of informal output and informal firms in the economy, while ρ and σ_ν mainly affect the firm size distribution moments. On the other hand, $\bar{\ell}$ and θ mainly determine the entrepreneurship and self-employment rates. Table 3 shows the most informative moment for each internally calibrated parameter.

Table 3: Internally Calibrated Parameters.

Parameter	Description	Moment
p_1	Detection probability (intercept)	Informality rate (output)
p_2	Detection probability (slope)	Informality rate (firms)
$\bar{\ell}$	Owner labor	Entrepreneurship rate
θ	Variable cost of employees	Share informal firms ≤ 1
ρ	Persistence shock	Share informal firms ≤ 2
σ_ν	Standard deviation shock	Share formal firms ≤ 5

III.D Calibration Results

Model fit. Table 4 shows the model fit over targeted dimensions and the associated parameter values. The model replicates well the share of informal output, the entrepreneurship rate and the informal firm size distribution moments, while it slightly underestimates the share of small (at most 5 employees) formal firms (62% in the model compared to 70% in the data) and it overestimates the share of informal entrepreneurs (84% in the model compared to 76% in the data).

Table 4: Data and Model Statistics over Targeted Dimensions.

Parameter	Value	Target	Model	Data
p_1	244.69	Informality rate (output)	0.36	0.36
p_2	3.55	Informality rate (firms)	0.84	0.76
$\bar{\ell}$	0.17	Entrepreneurship rate	0.34	0.30
θ	0.14	Share informal firms ≤ 1	0.84	0.83
ρ	0.97	Share informal firms ≤ 2	1.00	0.95
σ_ν	0.06	Share formal firms ≤ 5	0.62	0.70

Table 5 displays how the model performs over some dimensions that are not targeted. These variables are the informality rates for self-employed and small firms (at most 5 employees), additional moments of the formal firm size distribution, including average firm size, and some public finance statistics.[8] Despite these variables are not targeted in

8. As pointed out by Erosa, Fuster, and Martinez (2023), it seems more correct to compare sales tax revenues in the model to the sum of sales and income tax revenues in the data, since there is no income tax in the model.

the calibration, the model replicates them fairly well.

Table 5: Data and Model Statistics over Untargeted Dimensions.

Moment	**Model**	**Data**
Informality rate among self-employed	0.90	0.92
Informality rate among firms ≤ 5	0.90	0.84
Share formal firms $6-10$	0.12	0.14
Share formal firms $11-20$	0.16	0.08
Share formal firms $21-50$	0.08	0.05
Share formal firms $50+$	0.02	0.03
Average firm size	2.08	2.39
Sales tax/GDP	0.20	0.17
(Sales tax + Income tax)/GDP	0.20	0.24
Payroll tax/GDP	0.07	0.07

Data source: Own calculations based on ECINF (2003), tabular data from RAIS, Bento and Restuccia (2021) for average firm size, Erosa, Fuster, and Martinez (2023) for taxes.

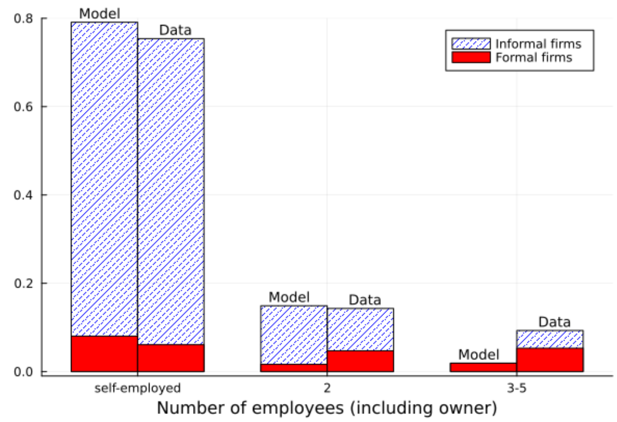
How does the model replicate the informality rates and the shares of small firms across different size categories? Figure 2 depicts the shares of formal and informal firms for self-employed, firms with 2 employees (including the owner), and firms with 3-5 employees in the model (left columns) and in the data (right columns). While the model replicates well the informality rate for self-employed (90% v. 92% in the data), it overestimates it for firms with 2 employees (89% v. 67%) and it underestimates it for firms with 3-5 employees (0% v. 43%).

Further model implications. To conclude the model fit analysis, I present further statistics that do not have an exact analogous in the data but that replicate well-known patterns of Brazilian and other developing countries' economies.

Figure 3 shows the relationship between the number of employees and the probability of detection from the tax authority. The detection probability for a self-employed agent is between 1% and 7%[9], whereas it dramatically increases as employment goes up. In fact,

9. Notice that number of employees is a continuous variable in the model, therefore the detection probability of a self-employed agent is not constant. In the model, a self-employed agent is defined as such if $\bar{\ell} + n \leq 1$.

Figure 2: Informality Rates for Small Firms.



Data source: Own calculations based on ECINF (2003).

the detection probability increases up to 73% for a firm with 2 employees and to 100% for a firm with 5 employees. This is consistent with the fact that about 95% of informal firms have two employees (including the owner) or less in the Brazilian data.

Figure 3: Probability of Detection for Different Levels of Employment.

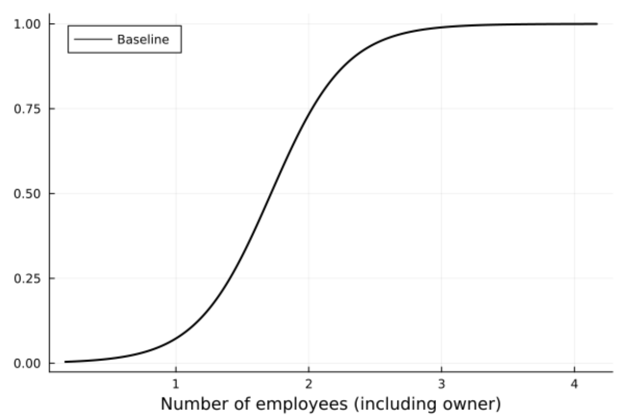
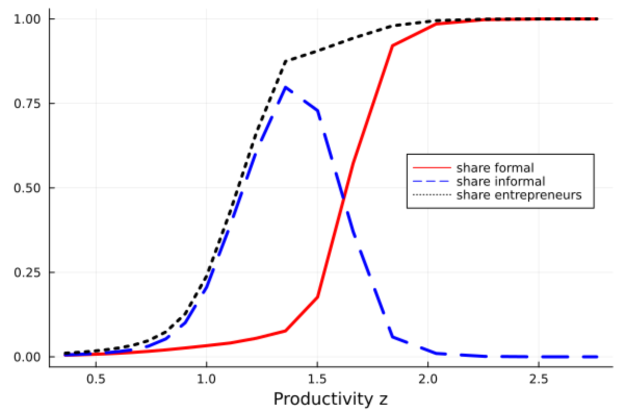


Figure 4 shows the share of formal (red solid line) and informal (blue dashed line) entrepreneurs over different levels of the productivity distribution. The dotted black line represents the overall share of entrepreneurs. For each share, the denominator is the total number of agents in the economy. The graph points out that informality is the preferred choice for entrepreneurs with low levels of productivity, but this preference is reversed as we move to the right of the distribution.

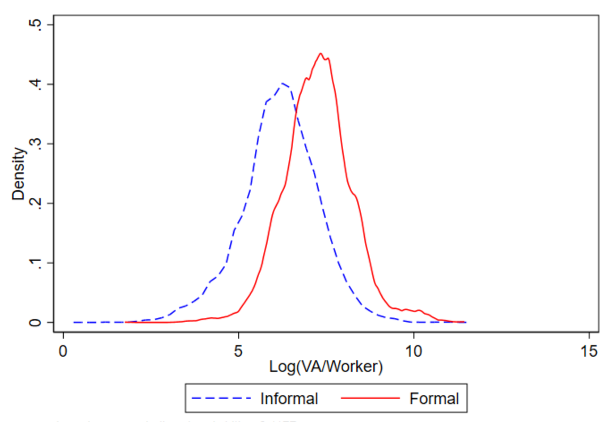
The graph is consistent with two patterns observed in the data: (i) more productive agents

Figure 4: Share of Formal, Informal, and Entrepreneurs over the Productivity Distribution.



tend to be entrepreneurs rather than workers, and (ii) formal entrepreneurs are on average more productive than informal entrepreneurs. The latter pattern is observed in cross-country data (for example, La Porta and Shleifer (2014)) and in Brazilian data as well. In fact, Figure 5 depicts the productivity distributions of formal (red solid line) and informal (blue dashed line) firms with at most 5 employees in the ECINF data. Productivity is approximated as value added per worker.

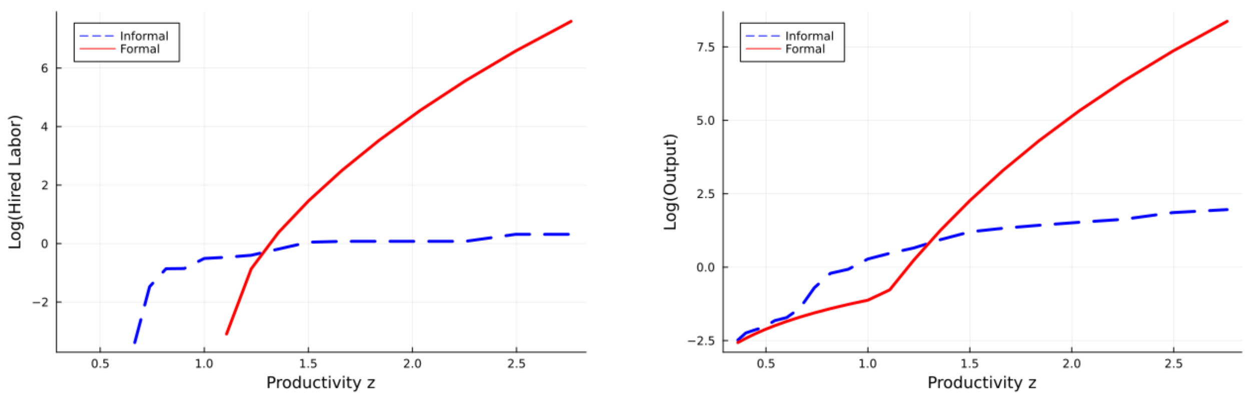
Figure 5: Kernel Distribution of Productivity for Small (≤ 5) Formal and Informal Firms.



Productivity is measured as value added per worker (in logs). Source: Own calculations based on ECINF.

Finally, Figure 6 shows optimal labor and output policies for formal and informal entrepreneurs. In addition to the composition effect in productivity already described, informal entrepreneurs hire fewer employees compared to formal entrepreneurs with the same level of productivity (panel a). The reason for this behavior is to avoid detection from the tax authority. Consequently, the optimal choice of output is also lower for a given level of productivity (panel b).[10]

Figure 6: Employment and Output for Different Productivity Levels.



(a) Log of employment over the productivity distribution for formal and informal.

(b) Log of output over the productivity distribution for formal and informal.

IV Quantitative Experiments

In this section, I perform some counterfactual experiments to assess the effects of tax enforcement on the variables of interest. The purpose of these exercises is to estimate the extent to which variations in tax enforcement, indirectly measured through variations in informality, can account for the observed differences in output, TFP, and average firm size. In the experiments, I vary the parameter p_1 of the detection probability function to match other countries' informality rates. I also adjust the sales tax rate τ_y to keep total revenues as close as possible to the baseline amount. All other parameters remain unchanged. Therefore, we can interpret the counterfactual economy as a version of the Brazilian economy characterized by a counterfactual tax enforcement.

10. This is not true for a few low productivity values. At these values, formal firms have to pay (distortionary) taxes, while informal firms do not and face a probability of detection that is close to 0. However, this effect tends to be quantitatively small in the aggregate, given the low mass of formal firms at these productivity levels.

IV.A Main Counterfactual

The main counterfactual matches the informality rate of the GDP-weighted average of the six largest Latin American economies, namely, Argentina, Chile, Colombia, Mexico, Peru, and Venezuela. The last column in Table 6 shows the average statistics for the counterfactual economy. The informality rate stands at around 30%, 6 percentage points lower than in Brazil. GDP per capita and TFP are about 32% and 6% higher than in Brazil. Finally, average firm size is 3.45, compared to 2.39 in the baseline.

In order to match the lower informality rate, the parameter p_1, which controls the inflection point of the detection probability function, goes down from a value of 245 to a value of 184. Figure 7 shows the probability of detection function as a function of number of employees in the baseline (black solid line) and in the counterfactual economy (gray dashed line). The probability of detection for a self-employed and for a firm with two employees are as high as 9% and 79%, respectively, compared to 7% and 73% in the baseline.

Figure 7: Probability of Detection for Different Levels of Employment, Baseline and Counterfactual.

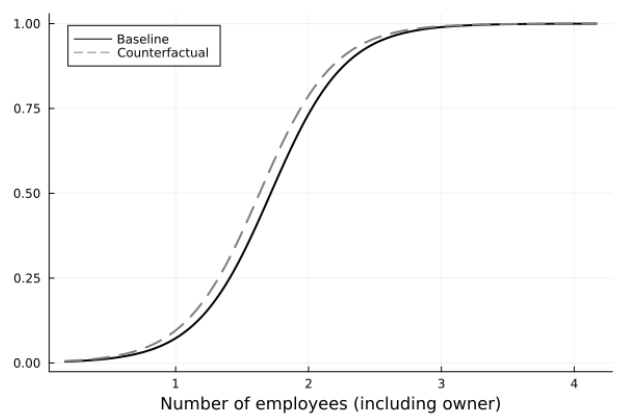


Table 6 points out that a stricter tax enforcement results in increased output, TFP, and average firm size. Compared to the baseline, output increases by 4.3 percentage points, which accounts for 13% of the measured difference in GDP per capita in 2003. TFP also goes up by about 0.5 percentage points, which is approximately 9% of the measured difference in TFP in 2003.[11] Average firm size increases from 2.08 in the baseline to 2.37 in the counterfactual. Bento and Restuccia (2021) estimate average firm size to be 2.39 in Brazil, while the figure for the GDP-weighted average of the six countries considered is 3.45. Therefore, stricter tax enforcement accounts for almost 30% of the estimated differences in average firm size. In this experiment, I change the sales tax rate to $\tau_y = 0.268$ ($\tau_y = 0.293$

Table 6: Matching Counterfactual's Weighted Average Informality Rate - Counterfactual Moments. Share Accounted for by the Model in Brackets.

Variable	**Brazil**		**Counterfactual**	
	Model	**Data**	**Model**	**Data**
Informality rate	0.365	0.360	0.296	0.298
GDP per capita	1.000	1.000	1.043 [13.2%]	1.325
TFP	1.000	1.000	1.005 [8.8%]	1.062
Average firm size	2.080	2.390	2.374 [27.5%]	3.450

The counterfactual economy's data are computed as GDP-weighted averages of Argentina, Chile, Colombia, Mexico, Peru, and Venezuela. Source: own calculations based on Elgin et al. (2021) (informality), Feenstra, Inklaar, and Timmer (2015) (GDP per capita and TFP), and Bento and Restuccia (2021) (average firm size). Data are for 2003 except for average firm size.

in the baseline) to maintain total revenues close to the baseline amount. Therefore, the experiment suggests that stricter tax enforcement would not only reduce the level of informality but also allow for the reduction of taxes that are inefficiently high for the most productive agents in the economy.[12] Note that the model assumes that the tax authority does not incur any cost associated with tax inspections. However, if I introduced a constant inspection cost per firm, the total enforcement cost would not necessarily exceed that of the baseline economy, since fewer firms would operate informally.[13]

11. In the model, TFP is measured according to the formula $TFP = \frac{Y}{(K^\alpha(L+s_e\bar{\ell})^{1-\alpha})^\gamma}$, where K. L, and Y denote aggregate capital, labor, and output, whereas s_e is the share of entrepreneurs in the population.

12. It has been documented that several developing economies are characterized by the coexistence of high informality rates and high tax rates (for the minority of agents and firms paying taxes).

13. An alternative approach would be to model inspection costs as decreasing in firm size, reflecting the greater difficulty of detecting micro firms. However, incorporating such a specification would require data on the distribution of inspections across informal firms, which are currently unavailable.

IV.B Additional Experiments

This section describes additional quantitative experiments taking different countries or group of countries as counterfactuals. Besides considering single countries such as Argentina and Chile, I also perform an exercise that takes GDP-weighted average informality of a larger group of Latin American countries as counterfactual.[14] As for the previous exercise, the detection probability parameter p_1 is changed to match the correspondent level of informality for each country or group. I then compare model-implied GDP-weighted averages of GDP per capita, TFP, and average firm size with their measured counterpart.

Results of the counterfactual experiments are shown in Table 7. The top half displays measures of informality, GDP per capita, TFP, and average firm size for each country and group of countries. The bottom half presents the corresponding model-implied statistics. The percentages in brackets denote the shares of the measured differences in the variable of interest that are accounted for by the model.

Table 7 suggests that tax enforcement differences account for a relatively large fraction of the observed differences in average firm size, ranging from a minimum of 21.0% (Group 2) to a maximum of 71.5% (Mexico). On the other hand, the effects on GDP per capita and TFP account for a smaller fraction, ranging from a minimum of 8.3% and 3.3% (Mexico) to a maximum of 37.6% and 26.4% (Chile).

The low effect on TFP requires further discussion. It is important to remember that the only parameters that differ across experiments are the detection probability parameter p_1 and the sales tax rate τ_y, while all the other parameters have the same value as in the baseline Brazilian economy. Importantly, the invariant distribution of the productivity process is kept constant across experiments. Therefore, differences in aggregate productivity can only stem from heterogeneity in occupational choices and in capital and labor policy decisions. It can be argued that at least part of the observed differences in TFP is

14. The group includes 17 countries: Argentina, Bolivia, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay, Venezuela.

Table 7: Effects of Tax Enforcement. Data and Model Statistics, Share Accounted for by the Model in Brackets.

Country	Informality (1)	GDP pc (2)	TFP (3)	Average Size (4)
Data				
Brazil (*Baseline*)	0.36	1.000	1.000	2.39
Group 1 (*Main*)	0.30	1.325	1.062	3.45
Group 2	0.31	1.248	1.051	3.42
Argentina	0.23	1.334	1.104	4.14
Chile	0.19	1.307	1.050	5.67
Mexico	0.29	1.567	1.187	2.83
Peru	0.55	0.633	0.675	2.45
Model				
Brazil (*Baseline*)	0.36	1.000	1.000	2.08
Group 1 (*Main*)	0.30	1.043 [13.3%]	1.005 [8.8%]	2.37 [27.5%]
Group 2	0.31	1.034 [13.9%]	1.004 [7.9%]	2.30 [21.0%]
Argentina	0.23	1.097 [29.1%]	1.012 [11.1%]	2.82 [42.1%]
Chile	0.19	1.115 [37.6%]	1.013 [26.4%]	3.04 [29.2%]
Mexico	0.29	1.047 [8.3%]	1.006 [3.3%]	2.40 [71.5%]
Peru	0.55	0.919 [22.1%]	0.975 [7.8%]	1.69 [n/a]

Source: Informality rates are from Elgin et al. (2021). GDP per capita and TFP are from Feenstra, Inklaar, and Timmer (2015). Average firm size are from Bento and Restuccia (2021). Data are for 2003 except for average firm size.
Group 1: GDP-weighted average of Argentina, Chile, Colombia, Mexico, Peru, Venezuela. Group 2: GDP-weighted average of Argentina, Bolivia, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay, Venezuela.

due to differences in the distribution of skills that cannot be accounted for by the model.

IV.C Economic Mechanisms

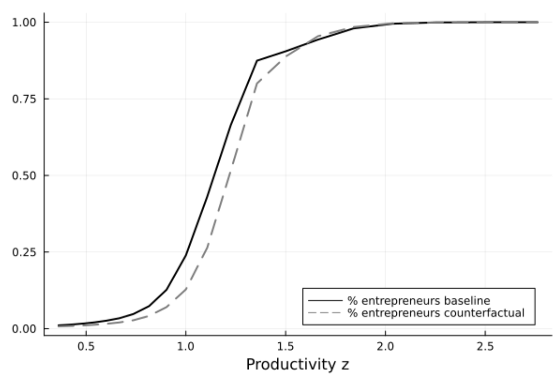
What are the underlying sources of the differences between the baseline and the counterfactual economies? To answer this question, it is useful to compare the occupational choices and the policy functions in the two economies. For illustration purposes, I will compare occupational and policy functions in the baseline and in the counterfactual where tax enforcement is such that it matches the Chilean informality rate (19%).[15] In the fol-

15. In this calibrated economy, $p_1 \approx 90$ and $\tau_y = 0.228$.

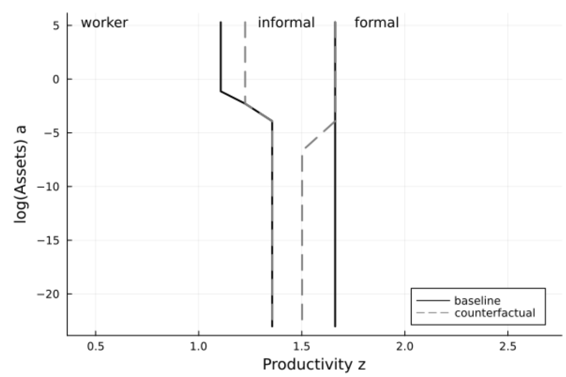
lowing graphs, the solid lines represent the values for the baseline economy, while the dashed lines represent the counterfactual values.

Figure 8 panel (a) shows that the share of entrepreneurs in the counterfactual economy is significantly lower for low values of productivity. Therefore, stricter tax enforcement leads to higher average entrepreneurial ability, inducing in turn a positive effect on average firm size given the positive relationship between firm-level productivity and size. Panel (b) displays occupational choices for different levels of productivity z (x-axis) and log-assets a (y-axis). The lines demarcate three areas, which correspond to combinations of productivity and assets where it is optimal to either be workers, informal entrepreneurs, or formal entrepreneurs.[16]

Figure 8: Share of Entrepreneurs and Occupational Choices.



(a) Share of entrepreneurs (formal and informal) over the productivity distribution.



(b) Occupational choices for different levels of productivity z (x-axis) and log-assets a (y-axis).

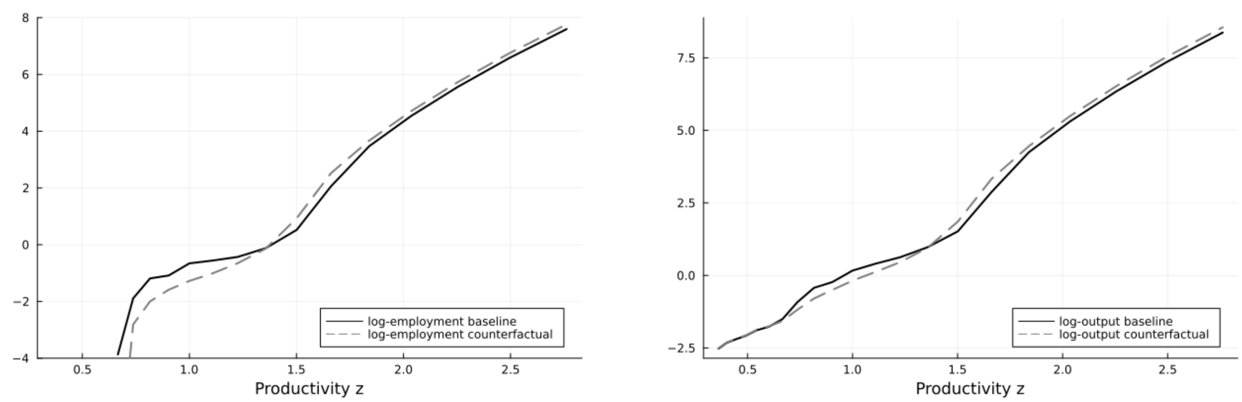
Notice that, for some values of productivity, agents with sufficient assets prefer to become informal entrepreneurs, while agents with low assets choose to be workers or formal entrepreneurs. This is due to the uncertainty in detection by the tax authority. In other words, for certain productivity values, the expected earnings are higher if agents decide to be informal entrepreneurs, but they only make this choice if they have enough assets. The graph shows not only that the share of entrepreneurs is lower in the counterfactual,

16. In reality, the presence of occupational shocks leads to a probability distribution over occupational choices for each combination of productivity and assets. Therefore, the graph represents the choice with the highest probability.

but also that the formality rate among entrepreneurs is higher. This is caused by a combination of stricter detection probability and lower tax rates. Taken together, the two panels suggest that informal entrepreneurs reallocate either as workers or as entrepreneurs in the formal sector.

The reallocation effect can also be observed in Figure 9, which depicts the average log-employment and log-output (conditional on being entrepreneurs) as a function of productivity in the two economies.

Figure 9: Employment and Output for Different Productivity Levels.



(a) Log of employment over the productivity distribution.

(b) Log of output over the productivity distribution.

Notice that employment and output are lower in the counterfactual economy for low values of productivity. There are two reasons for this pattern. First, for very low levels of productivity, formal firms tend to be smaller than informal firms. This is a consequence of the fact that small formal firms have to pay taxes, while small informal firms do not and face a detection probability which is close to 0. Second, as pointed out in Figure 7, for a given level of employment, informal firms face a higher detection probability in the counterfactual economy. Therefore, if they choose informality in the counterfactual economy, they might choose a lower scale to reduce the detection probability. However, these effects are quantitatively small in the aggregate and are more than compensated by higher values of labor and output for higher levels of productivity, as shown by the dashed line being on top of the solid line for both employment and output. The graphs point out to a reallocation of labor and output from low-productivity agents to high-productivity agents, which in turn leads to an increase in TFP and average firm size.

IV.D Decomposing Selection and Detection Channels

While in Section IV.C I presented a qualitative analysis of the channels through which tax enforcement affects the outcomes of interest, in this section I quantitatively assess the contribution of the two main channels—selection and detection channels—to the overall estimated impact. To decompose the effects, I shut down one channel at a time, and then compare TFP, output, average firm size, and other statistics when only some decisions are allowed to change. The counterfactual considered is the GDP-weighted average of the six largest Latin American economies (*group 1*).

Table 8 displays the decomposition. Since the invariant distribution $\mu(z, a)$ is different in the counterfactual, I first fix the distribution as in the baseline in columns (2) to (4), while I adjust it to the counterfactual distribution in column (5). The selection effect in column (2) is obtained by maintaining the capital and labor decisions and the share of informality for every productivity level as in the baseline while allowing the share of entrepreneurs to change as in the counterfactual. Since the number of entrepreneurs goes down and production for the remaining entrepreneurs remains constant, output mechanically decreases. Despite an increase in average entrepreneurial ability, TFP does not seem to be affected by the selection channel. On the other hand, average firm size increases from 2.08 to 2.16.

Column (3) displays the contribution of the detection channel, which is obtained by maintaining the same share of entrepreneurs as in the baseline while allowing changes in capital, labor, and formality status. The decrease in informality over the firm-level productivity distribution induces an overall increase in aggregate capital, labor, and output. Moreover, the reallocation of resources towards more productive and larger firms implies an increase in TFP.

Column (4) shows the sum of the two effects while keeping the same invariant distribution as in the baseline. Two properties stand out. First, the rise in output due to the detection channel more than compensates the negative impact of the selection channel.

Table 8: Decomposition of Selection and Detection Channels.

	Baseline (1)	(2)	(3)	(4)	**Counterfactual** (5)
Fixed decisions	-	ℓ, k, form.	% entr.	-	-
Distribution $\mu(z,a)$	-	Baseline	Baseline	Baseline	Counterfactual
Channels	-	Selection	Detection	Sel.+Det.	Sel.+Det.+Distr.
Outcome					
Output	1.000	0.982	1.078	1.061	1.043
Capital	4.54	4.44	4.98	4.88	4.78
Labor	0.66	0.65	0.71	0.70	0.69
TFP	1.000	1.000	1.004	1.007	1.005
Average firm size	2.08	2.16	2.24	2.33	2.37
Entrepreneurship	0.34	0.32	0.34	0.32	0.31
Informality (Firms)	0.84	0.84	0.82	0.81	0.82
Informality (Output)	0.36	0.35	0.31	0.30	0.30

Column 1: baseline. Column 2: fixed capital, labor, and formality status decisions, change in occupational choices allowed (*selection*). Column 3: fixed occupational choices, changes in capital, labor, and formality status decisions allowed (*detection*). Column 4: sum of both effects keeping the same distribution $\mu(z,a)$ as in the baseline. Column 5: distribution adjusted (main counterfactual).

Second, the interaction between the two channels seems to produce a positive effect on TFP and average firm size that is larger than the sum of the two channels taken in isolation.

Finally, in column (5), I allow the distribution to vary to obtain the counterfactual statistics already discussed in Table 6.

V Conclusion

This paper develops a quantitative framework to assess the impact of tax enforcement on average firm size and TFP. As tax enforcement becomes stricter, fewer agents choose to be entrepreneurs, and fewer entrepreneurs choose to operate in the informal sector. These mechanisms lead to a rise in average firm size and an improvement in allocative efficiency. Counterfactual analysis suggests that stricter tax enforcement in Brazil would result in sizable gains in average firm size, TFP, and GDP per capita. Considering several counterfactual experiments, the gains account for about 25-30% of the estimated differences in average firm size and for about 8-15% of the estimated differences in TFP and GDP per capita.

Therefore, this paper identifies tax enforcement as a relevant source of the observed cross-country differences in average firm size, TFP and GDP per capita.

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