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RESEARCH ARTICLE

Heterogeneous returns of informality: Evidence from Brazil

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Abstract

This paper estimates the marginal treatment effect of formality on wages for Brazil at the individual level leveraging regional data on labor inspections for identification. The results show that there is significant essential heterogeneity among otherwise identical workers that lead them to self-select into the type of jobs, formal or informal, that better reward their skills. The Average Treatment Effect (ATE) is 22%, but not statistically different from zero. But there are individuals with very low non-observed costs of formality that can earn premiums of up to 100% of their wage from being formal and workers who would be hurt if they switch from informality to formality as they experience very high non-observed costs of being formal. Two policy experiments in which we tighten enforcement of the labor law via hiring more labor inspectors increase the likelihood of workers being formal, but it has, on average, a negative effect on wages for the workers who are induced to switch from informality to formality.

Keywords: labor informality; labor regulation; enforcement; marginal treatment effects.
JEL codes: H26, J24, J32, J46, K31.

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1. Introduction

Informality is a widespread phenomenon in the developing world. In Brazil, approximately 40% of the GDP and 35% of employees are informal (Ulyssea, 2018); (Meghir et al., 2015). Similar statistics can be found across Latin America and even higher numbers in Africa. Governments and policy-makers care about informality and try to reduce it not only because it may hurt some workers as they do not have access to social protection benefits and job stability, but also because informality is not efficient from the point of view of the state. Informality hinders the ability of the state to collect taxes as there are no legal records that prove what is the real income of an individual or how much profit an informal firm makes (Meghir et al., 2015); (Bobba et al., 2022).

When it comes to informal jobs, these are commonly thought to be precarious and of bad quality. Informal workers are usually seen as individuals who could not get a formal job. But when looking at the individual level data on informality, the picture is not quite like that. Many informal workers around the world are informal because they choose to, not because that is their only option (Maloney, 2004); (Perry et al., 2007) (Levy, 2008); (Lehman and Muravyev, 2014).

This paper aims to estimate the heterogeneous returns of labor informality using an identification strategy that captures the cost of labor enforcement for Brazil by using variation in the number of labor inspectors at the state level, among other regional data. The results indicate that the higher the number of labor inspectors in a state, the higher the likelihood of individuals being formal, but being in a state with a larger urban area decreases the likelihood of being formal as inspectors now have to drive further distances and spend more time in each inspection. Thus, they perform fewer inspections per inspector. Regarding the effect on wages, workers self-select into the job type in which their skills are going to be better rewarded (formal or informal jobs). On average, the average treatment effect (ATE) of formality is 22% but it is not statistically different from zero, which implies that formal workers do not earn a premium, on average, but there are significant heterogeneous effects as workers with lower non-pecuniary costs associated with formality do earn very high premiums, up to 100%. Similar results are found for workers with a very high non-pecuniary cost of being formal, given that they would get hurt if they switch to formality as their skills are better rewarded in informal jobs. Therefore, informality in Brazil seems to respond to comparative advantage.

This paper fits into two strains of the literature on informality as it aims to understand why individuals are informal, but it also discusses the effects of regulation on informality. With respect to the first set of the literature, Magnac (1991) accounts for a stylized fact observed in developing countries in which a large portion of the population are informal, and some choose to be it by defining two views on informality. On one side, the segmented labor markets hypothesis that claims that there are labor market entry barriers and rigidities, such as minimum wages or tax laws, that restrict the access to the formal labor market so individuals with lower productivity are rationed out of the formal labor market as firms cannot afford to pay to them what the law requires. On the other side, there is the voluntary informality or comparative advantage hypothesis that states that workers self-select into informality after considering the costs and benefits associated to it versus a formal job.

For Latin America, authors like Perry et al. (2007) find that both views coexist as there are some workers who choose informal jobs after comparing their net benefit if they were to choose a formal job and there are also some workers rationed out of the formal labor market. **?** do the same for Argentina using marginal treatment effects, and they do not find any significant differences between the earnings of formal salaried workers and self-employed individuals once they account for selection, which is consistent with the comparative advantage hypothesis, but when comparing formal and informal salaried workers, they do find that informal salaried work carries significant earnings penalties so that result is more consistent with labor market segmentation. But, on the other side, Botelho and Ponczek (2011) study the Brazilian case by using fixed-effects model on a rotating panel and find that the average wage differential between formal and informal workers is 7.8%, which they take as a small degree of segmentation, but they only included in their sample employees at a firm.

Almeida and Carneiro (2012) study the impact that labor inspections have on the size of informality at the municipality level for Brazil. They show that although enforcement of labor regulation in the formal sector can increase labor costs and drive workers to informality, it is also true that labor inspections may enforce compliance with mandated benefits which are highly valued by workers, and potentially increase the attractiveness of the formal sector. They also find that in locations with frequent inspections, workers pay for mandated benefits by receiving average lower wages, but minimum wage policies prevent downward adjustment at the bottom of the wage distribution. Thus, formal jobs that pay low wages around the minimum wage become attractive to informal workers, inducing them to want to move to formality. This paper is the closest to us as we use a similar identification strategy, but the main difference is that we use individual level data given that we aim to recover heterogeneous returns of formality. In the same line, Viollaz (2018) measures the impact that changes in the enforcement of labor regulation have on compliance given firm size. The author finds that for Peru firms can reduce their size to benefit from lower fines and less stringent regulation, so in the end there is little to no effect of better enforcement on compliance.

Transitioning to search models, Meghir et al. (2015) show, using an equilibrium wage-posting model with heterogeneous firms, that there is evidence of compensating differentials in the wage schemes offered by informal firms when compared to the wages paid by formal firms of equal productivity. Contrary to what Almeida and Carneiro (2012) showed, this paper finds that tightening enforcement does not increase unemployment and can increase wages, total output, and welfare by enabling better allocation of workers to higher productivity jobs and improving competition in the formal labor market.

Haanwinckel and Soares (2021) develop a search and matching model of informal labor markets with worker and firm heterogeneity, intra-firm bargaining with imperfect substitutability across types of workers, and labor market regulation. Their model was calibrated using data from 2000 to 2012 and replicates the reduction in informality among salaried workers of around 10 percentage points that was experienced during that time, while the minimum wage increased by 61% in real terms. The authors argue that this could have happened due to a substantial increase in average years of schooling and TFP, which could have had their own equilibrium effects on informality. But since 2012 the Brazilian labor market has dramatically deteriorated, and informality has reached historically high rates (IBGE, 2019). Thus, the effect of the structural changes found by the authors (increased schooling and TFP) seem to not be persistent in time. In addition to that, their results show that at equilibrium firms and workers self-select into the formal/informal sector as the compensating differentials theory predicts. Firms do not want to comply with labor regulation, but non-compliance is too costly for large firms as they can be caught. Workers want to receive employment benefits but may be willing to accept informal jobs and leave unemployment for a sufficiently high wage. Minimum wages can also distort labor market allocations as if the minimum wage is binding for unskilled workers, they strictly prefer to have a formal job but are willing to accept an informal job in equilibrium to avoid unemployment. In this equilibrium, the formal wage premium decreases in the skill level, becoming negative for skilled individuals.

Ulyssea (2018) develops an equilibrium model where heterogeneous firms exploit two margins of informality: the extensive margin, in which firms do not register their business, and the intensive margin, in which firms hire workers “off the books”. The author uses Brazilian data to calibrate the model and finds that often firm and labor informality can move in a different direction as a response to a unique policy to promote formality. For example, a policy such as reducing the firm's entry cost to the formal sector, as Simples Nacional, induces firms to become formal, but then these newly created firms hire a large share of informal workers, so in the end there is zero effect on informal employment. On the other side, increasing enforcement of labor regulation reduces informality among workers but it increases informality among firms. Therefore, it is very important to study the effect of policies on the extensive margin, but also on the intensive margin as the effects of apparently good policies can be counterproductive.

The contributions of this paper are twofold. First, it uses a unique dataset on labor enforcement, which includes information about the number of labor inspectors in 2015, number of labor inspection offices in 2015, and other regional characteristics of the state that may affect enforcement. Second, it recovers the marginal treatment effect of formality on wage rate, which shows that although the ATE is 0.22 but not statistically significant, there is significant sizable heterogeneity in the returns to informality, with some formal workers earning wage premiums of more than 100%.

The paper is divided as follows. Section 2 describes very thoroughly the Brazilian labor market code, its legal implications when it comes to violation of the law about formality, and how it is enforced. Section 3 describes the data and shows descriptive statistics. Section 4 contains the empirical model we use and discusses the identification strategy. Section 5 includes results. Section 6 shows robustness checks that support our findings and section 7 talks about policy experiments. And Section 8 concludes.

2. Labor Market Regulation and Enforcement in Brazil

2.1. Labor Market Regulation

The social security system in Brazil has three components: health, social insurance (previdência social), and social assistance. The health and social assistance components are not contributory as they are financed through general taxation, so all Brazilians have access to them. The social insurance is mostly contributory. It includes benefits such as pension for those who reach the target age (60 years old for women and 65 for men) or those who reach the target number of years contributing to the system (30 years for women and 35 for men, regardless of their age), disability pension, death pension, sickness and maternity leave, and severance payments.

Employees must contribute 8% to 11% of their monthly wage to social insurance. On the other hand, urban employers must contribute every month 20% of the wage paid to their employees and rural employers contribute 2.85% of their billed revenues. And finally, self-employed and own account workers earning a minimum wage must contribute 5% or 11% depending on if they are covered by one of the special plans for low-income individuals, and those who earn more than a minimum wage or are not classified into any of the special plans must contribute 20% of their earnings (SPREV, 2017).

In Brazil, every single individual who works as an employee in any economic activity or works as a domestic worker must have a "Carteira de Trabalho" or worker's card, which is a document that guarantees that the worker has been hired formally, there is a registration about it in the worker's roster and accounting books of the firm, and there are contributions made to the social insurance on behalf of the worker. Thus, If the individual is formally hired and has a signed worker's card, she has guaranteed access to all the social insurance benefits.

If the person does not work at a firm or does not have a signed worker's card, she can also contribute to the social insurance as an own-account worker, and this gives her access to the same benefits if she is not under one of the two special regimes for low-income workers. The difference, though, is that as an own-account worker she must contribute up to 20% of her monthly earnings, and when employees have a signed card, they only contribute 8% to 11% of their monthly wage.

Additionally, self-employed individuals, entrepreneurs, and contractors (which usually operate as regular employees as it will be discussed later) must be registered at the Cadastro Nacional de Pessoa Juridica (CNPJ), which is the national registry of entities that pay taxes and social insurance contributions. Not being registered at CNPJ when working as a self-employed or entrepreneur is illegal.

Thus, an employee who does not have a signed worker's card or a self-employed individual or entrepreneur who is not registered at CNPJ is considered informal in this paper.

2.2. Violations of the Labor Code

Informality can come in many different flavors in Brazil. In this paper, as discussed earlier, we will focus on a legalistic approach that uses a clear-cut definition for informality. An individual is classified as informal if this person works as an employee in a firm or as a domestic worker and she does not have a signed worker's card, or if the person declares to be self-employed or an entrepreneur but does not have a registration in the CNPJ, which basically means constituting a single-person firm.

Thus, such types of violations are very common as it is frequently found that employers hire workers and do not sign their worker's card to avoid paying their portion of the social insurance. This is especially true for domestic workers, given that it is harder for labor inspectors to target houses in which they are working. Usually, when a domestic worker is an informal employee, the violation is caught because the inspectors knew about the irregularity through a complaint made by the worker herself. Self-employment is also highly informal as it is hard for inspectors to keep track of the economic activity of each citizen of the country.

Another source of informality that we want to explore in this paper comes from apparently formal self-employed individuals. In this case, firms hire workers under the figure of "contractors", which means that this worker is not an employee of the company, so she does not have a signed worker's card but a registration in the CNPJ. This version of hiring per se is not informal, but these individuals work as employees in practice, without distinction from regular employees. Thus, firms hire them under this figure to avoid paying social insurance taxes, as in this case the worker must assume 100% of the cost of the social insurance contribution.

Regarding said aspect, we will use a more flexible definition of formality as a robustness check given that some individuals who are hired as contractors and work in practice as employees are registered at CNPJ. So, they are classified as informal under the main definition used in this paper as they should have a signed worker's card, but in an alternative definition of formality (lax definition) we will classify as formal those workers who work as if they were employees, but they are contractors if they are registered at CNPJ.

There are other violations to the labor code besides not having a signed worker's card or a valid registration at the CNPJ. For example, the number of working hours is set to 44 hours per week by the Federal Constitution, but many employees end up working more hours than the legally established. The minimum wage is also another source of violation as we can see in the data that there were a significant portion of the employees with earnings below the minimum wage (R$ 788 monthly, equivalent to USD$296, or R$3.58 per hour which is equivalent[1] to USD$1.34), but we will not focus on them as that is out of the scope of this paper.

2.3. Enforcement

The Brazilian Constitution of 1988 established that the Ministry of Labor must hire labor inspectors (Auditores Fiscais do Trabalho - AFT) to execute and organize labor inspections that guarantee the right to a safe job. Thus, the Secretary of Labor Inspections, which is an office within the Ministry of Labor, oversees establishing the guideline for labor inspections in Brazil, formulating social programs to protect workers, and promoting the enforcement and compliance of the labor code. Additionally, the Secretary of Labor Inspections created in 2013 the Escola Nacional da Inspeção do Trabalho, Enit, which is a government-sponsored technical institution that offers on-the-job training for labor inspectors (ENIT, 2021).

Inspections take place under two scenarios: complaints from workers to the labor office or random inspections. Inspectors check the status of the workers cards to make sure they are properly signed, registration of the workers in the labor books of the company, and that workers are in a safe environment covered by all the laws included in the labor code.

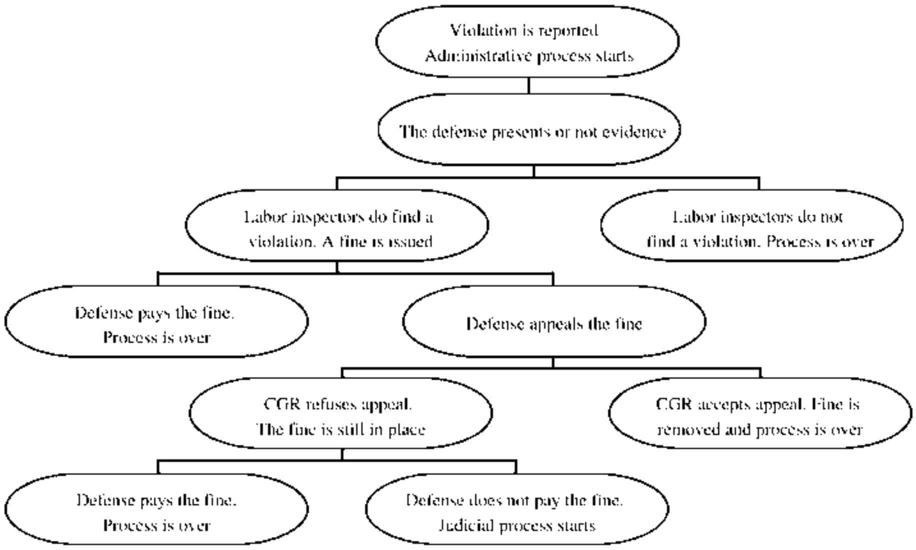
In 2017, 235.000 firms were inspected across the entire country, which is equivalent to approximately 5% of all the firms in Brazil. Given that there is a shortage of inspectors in Brazil, then most of the visits are scheduled after a complaint. When the inspection is done, if the inspector found an actual violation, then an administrative process starts. As Figure 1 shows, when the administrative process starts, the employer or worker has 10 days to present her defense. Then a designed labor inspector checks the arguments presented by the defense in case there was one and decides the validity of the argument to rule if there should be a fine or not. If the infraction was found to be valid, then the defense must pay a fine for it. If she pays in the following 10 days, there is a 50% discount in the amount of the fine (Cardoso and Lage, 2005). If the defense does not pay, she can appeal the fine and a new process starts again. If the person was found guilty of the violation, then she must pay the fine without any discount. If the individual does not pay the fine, the federal government immediately registers this person into the database of individuals who own money to the government and this action can have serious consequences such as the person not being able to get a job in the public sector.

The magnitude of the fines related to not having a worker's card or not having a signed worker's card with an entry of the current job is around US$103.9 or equivalent[2] to R$402.53. This amount of money doubles for every infraction that the inspectors find in a company or for every relapse.

[1]Using the official exchange rate of January 1st, 2015

[2]Using the exchange rate of January 1st, 2015

Figure 1: *Process for violations and penalties.*



Source: Secretaria de Trabalho (s.f)

3. Data Description

This study uses data from Pesquisa Nacional por Amostra de Domicilios (PNAD) for 2015, which is a household survey with information about workforce indicators, migration, and socio-economic characteristics. Additionally, it uses data from Instituto Brasileiro de Geografia e Estatística (IBGE) for regional indicators about GDP, number of firms, area of the states, among others. A full list of variables and its description can be found in the appendix.

In 2015, 356,904 individuals were surveyed by PNAD. The sample of this study only includes individuals who are between 20 and 60 years old (156,529 observations were dropped), who do not have a job in agricultural activities as their main job (16,340 observations were dropped), and who get a salary or receive a payment in monetary terms for their work (58,878 observations were dropped). Additionally, we only include in the sample individuals who are currently working and can be classified as formal or informal based on our definition (12,393 observations were dropped), who do not have missing values for their reported earnings (1,436 observations were dropped), who worked at least 20 hours in their main job if they claim to be formal employees or 5 hours if they are not employees (2,696 observations were dropped), who are not in the top and bottom 1% of the earnings distribution (1,759 observations), and who did not have missing covariates (1,676 observations were dropped). The final sample has 105,197 unique observations.

Formality is defined as an employee or domestic worker who has a signed worker's card or a self-employed or entrepreneur who is registered at the CNPJ. Secondly, informality is defined as a domestic worker or employee who does not have a worker's card and a self-employed or entrepreneur who is not registered at the CNPJ. Under this definition, "contractors", who work as if they were employees of a firm but instead of having a signed worker's card, they have CNPJ (which is cheaper to pay for both the employer and the employee), are classified as informal. We will use a more flexible definition of formality that includes those contractors as formal workers as a robustness check.

3.1. Descriptive Statistics

The informality rate in the sample is 37.9%, which is slightly lower than the informality rate at the country level that is 45% (IPEA) for 2015. When comparing these numbers with the informality rate in other Latin American countries, Brazil has an average rate. But if we compare such rate with the informality rate in developed countries or even with Chile, then Brazil has a high informality rate, on average, 20 to 30 percentage points higher. Work categories used in this paper only rely on the information provided by respondents when asked about their main job. The main job was defined as the work activity in which the individual spent most of her time during the reference year. In this regard, 64% of the sampled individuals are self-classified as employees, 23.3% are self-employed, 8.5% work as domestic workers, and 4% are entrepreneurs (Table 1). To be classified as an entrepreneur, the person has to have at least one employee working for themselves.

Table 1: *Job occupation included in sample*

Worker type	Formal	Informal	Total
Domestic worker	3,153	5,844	8,997
Employee	52,885	14,509	67,394
Entrepreneur	3,559	670	4,229
Self-employed	5,634	18,943	24,577

Source: Author's calculation

In general, individuals with formal and informal jobs have different demographic characteristics as can be seen in Table 2. There are slightly more women working informally than men and informal workers tend to be slightly older, on average. There are more married people with formal jobs than with informal jobs. Education differences are very important as formal workers tend to be more educated than informal workers. The biggest difference comes from the percentage of individuals who only have primary school or less, which is tremendously different between the two groups. Racial differences also play an important role in Brazil. Those who self-identified themselves as "White" and "Asian" work mostly as formal workers, but Afro-Brazilian workers have informal jobs in a higher proportion.

As we excluded from the sample those who work in agricultural jobs, then the sample over-represents urban workers. Regional differences are also important in Brazil as the largest economic centers are in the Southeast region, such as Sao Paulo and Rio de Janeiro. The North and Northeast regions are traditionally poor, and they have the largest shares of minority groups.

3.2. Labor Market Variables

Wages in Brazil are, on average, relatively low and exhibit very high variance. For 2015, the legal monthly minimum wage was established at R$788 or US$199. This wage applies to workers who work 44 hours per week. Around 50% of the Brazilian workers earn the minimum wage or less.
In the sample, the average monthly earnings were R$1,586. But as we can see in Table 3, formal workers have monthly earnings that are 40% higher than those of informal workers. There is a mass concentration of individuals around the minimum wage cut-off (vertical line in Figure 2). Earnings also differ greatly by educational level, self-declared ethnicity, and state. For example, self-reported Asian individuals earn, on average, R$2,814, but Afro-Brazilian individuals earn, on average, R$1,297 monthly.

Weekly hours worked are higher for formal workers, but informal workers have higher variance.

Table 2: *Descriptive Statistics – Part I*

Variable	Formal	Informal	t-test
Female	0.424	0.457	10.36
Age at the time of survey	36.7	38.3	23.88
	(10.7)	(10.3)	
Married	0.639	0.559	-25.73
Schooling level			
Primary school or less	0.256	0.447	65.3
High school	0.477	0.384	-29.53
College	0.255	0.162	-35.5
Graduate school	0.01	0.005	-8.88
Ethnicity			
White	0.474	0.359	-36.85
Afro-Brazilian	0.103	0.116	6.29
Asian	0.004	0.002	-5.68
Mixed	0.414	0.518	33.05
Indigenous	0.002	0.003	3.01
Urban	0.958	0.91	-31.71
Region			
North	0.101	0.189	40.78
Northeast	0.212	0.309	35.4
South	0.21	0.121	
Southeast	0.36	0.271	-30.23
Center	0.122	0.142	9.09

Source: Author's calculation

Formal workers report to work 43 hours per week and informal workers report 37 hours per week. The wage rate, which is our variable of interest, is also different between the two groups. Formal workers have a higher wage rate on average, which is roughly equivalent to US$2.98 per hour. The participation rate in Brazil in 2012 was 63.7%, on average, but after the economy started to deteriorate, the participation rate went down 9 percentage points to 56.8%. Differences in participation rate between men and women diminished between 2012 and 2016 (Table 4).

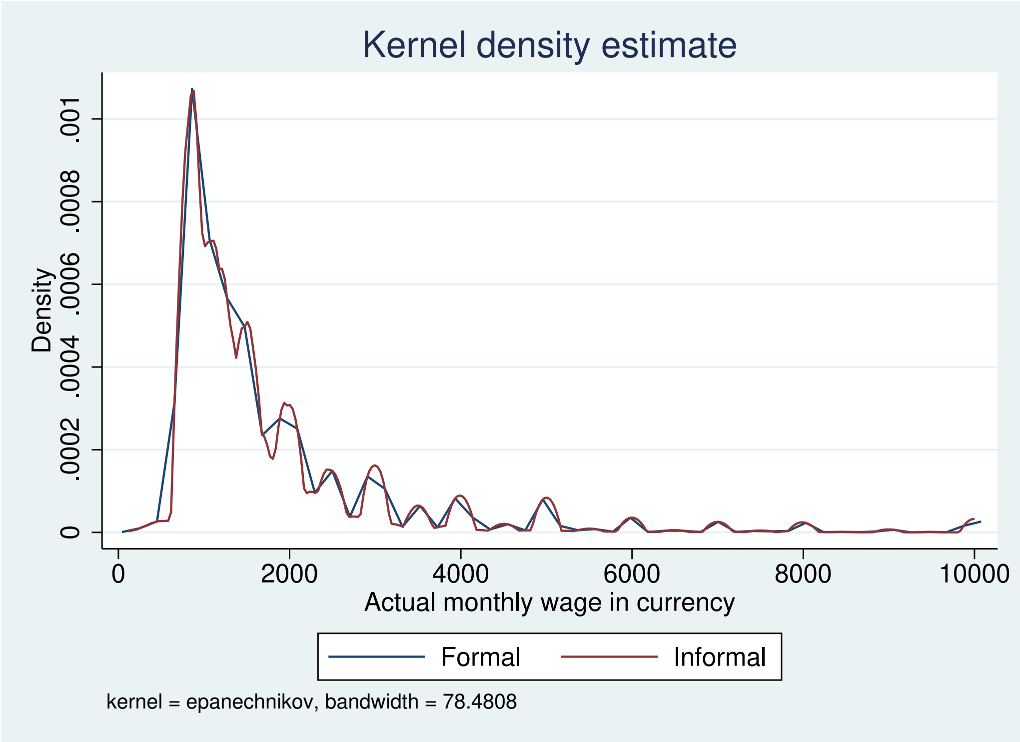
The unemployment rate before 2015 was in the single-digit units and stable, but since 2015 it started climbing because of the economic crisis the country has been experiencing in the past few years. In 2016, the unemployment rate was 12%. (Table 5).

3.3. Labor regulation variables

Informal individuals tend to be more concentrated in states that are less developed, with fewer firms, and fewer inspection offices and inspectors (Table 6). On average, 8% of the firms in a state are inspected, but as it was previously explained, the inspection process although it has a random component it usually works through calls and complaints.

For 2015, there were 2,466 inspectors for the whole country, distributed among the 26 states of the country and the federal district, Brasilia. On average, states have 91 inspectors and 5 offices, but these results are skewed by the presence of states from the Southeast region (Sao Paulo, Minas Gerais, and Rio de Janeiro), in which there are 1,012 inspectors. This is expected as it is in these states in which

Figure 2: *Kernel Distribution Monthly Earnings*



Source: Author's calculation

most of the economic activity of the country happens. Sao Paulo state alone produces more than 30% of the GDP of Brazil.

4. Econometric Framework

This section introduces the empirical methodology used in the paper. First, it briefly discusses why traditional OLS methods are not appropriate in this scenario. Then, it introduces the marginal treatment effect model used for estimation and discusses the requirements for having identification of the parameters of interest under the MTE model.

4.1. OLS and Instrumental Variables (IV)

Under OLS, the estimation of the returns of informality, , would be consistent only if informality is not correlated with the error term, ϵ, conditional on X.

$$Y = X^{'}\beta + D + \epsilon$$

Where Y is log wage rate, X are exogenous covariates, D is a binary variable that takes the value of 1 if the individual is formal and 0 if informal and ϵ is an error term.
But if informality is not randomly assigned and it depends on the characteristics of the individuals, then the self-selection process should be modeled as the coefficient of interest, in this case, is biased and it suffers from "selection bias". Thus, the selection process can be represented by the following equation:

Table 3: Descriptive Statistics - Part II

Variable	Formal	Informal	t-test
Hourly wage rate (in Brazilian reals)	11.6	9.27	-34.13
	(11.35)	(9.65)	
Labor earnings per month	1813.16	1217.06	-68.7
	(1,499.22)	(1,114.09)	
Weekly hours worked	42.92	37.33	-85.64
	(7.96)	(13.2)	
Average monthly earnings by state	1,833.32	1,699.13	-63.06
	(338.64)	(338.64)	

Note: On December 31, 2015, USD$1 was equivalent to R$3.96. Source: Author's calculation.

Table 4: Labor Force Participation rate for 2012-2016

Year	Total	Women	Men
2012	63.7	52.5	76
2013	59.4	48.3	71.7
2014	59.2	48.3	71.2
2015	58.5	47.8	70.3
2016	56.8	46.7	67.8

Source: (IBGE, s.f)

$$D = Z^{'}\gamma + v$$

Therefore, we need to take into consideration the selection process into informality and correct for it the outcome equation to recover a consistent estimator in the presence of selection. Additionally, if the returns to informality vary based on observable and unobservable characteristics of the individual, as it was stated in the introduction, then traditional selection methods will not suffice as it is important to capture this attribute of the data in the empirical model by recovering not only mean effects, but the whole distribution of the effect of informality on the wage rate. As Heckman and Vytlacil (2005) show, then self-selection may arise in two forms: selection based on heterogeneous background and characteristics, which is the "selection bias" problem, and also the "selection on gains" problem, which is when the people who select into formality are the ones who expect the highest gains from it, so the returns of the treatment are not the same for similar individuals.

4.2. Marginal Treatment Effect Model

Let Y be the observed outcome of interest, the log real wage rate at main job. Assume that there are two types of occupations indexed by two labor market sectors: formal (treated state) and informal (untreated state). Let D represent the binary treatment of interest: being formal. Define Y_1 as the potential outcome of an individual in the treated state $(D = 1)$ and define Y_0 as the potential outcome of an individual in the untreated state $(D = 0)$, such that Y_1 represents the potential wage rate of an individual who works formally, and Y_0 represents the potential wage rate of someone who works informally.
This gives rise to a switching model that can be expressed as the following:

$$Y = (1 - D)Y_0 + DY_1 \tag{1}$$

Table 5: Unemployment rate for 2011-2016

Year	Unemployment rate
2011	6.0%
2012	7.4%
2013	4.1%
2014	6.8%
2015	8.5%
2016	12%

Source: (IBGE, s.f)

Table 6: Descriptive Statistics on Inspections and Regional Data

Variable	Mean /(St. Dev.)
Population at state	7,572,246
	(8,995,884)
State GDP per capita	24,963.88
	(13,365.99)
Number of inspectors per state	91.33
	(92.89)
Number of inspection offices in the state	5.29
	(6.37)
Number of firms in the state	184,052.4
	(303,997)
Number of inspected firms at state	8,740.29
	(9,176.77)
State urban area in squared km	21,396
	(1,022.36)
Ratio of urban area to inspectors per state	761
	(350)

Source: Author's calculation

Following Carneiro et al. (2011), this estimation method is based on the generalized Roy Model of occupation choice. The decision rule of an individual i to work formally or informally is characterized by a latent variable model Willis and Rosen (1979):

$$Y_1 = X^{'}\beta_1 + U_1$$
$$Y_0 = X^{'}\beta_0 + U_0$$

where X contains sociodemographic characteristics such as schooling, age, parents' education, and regional controls, The decision rule of an individual i for choosing between a formal or an informal job can be characterized by a latent variable model Willis and Rosen (1979):

$$D = 1(D^{*} > 0) \tag{2}$$

where: $D^{*} = Z - V$

D equals one for individuals who work formally and zero for individuals who work informally. Z is a vector that contains observable individual and family characteristics that affect the decision to work formally or informally, and it also includes exclusion restrictions, which affect the decision of being formal but not earnings directly. The inclusion of these variables is what allows us to get identification. V represents the unobserved marginal cost of being formal. Notice that as V is a cost, it could be interpreted as the cost of having a less flexible job or being in a dependent working relationship when the individual has strong entrepreneurial skills, among others.

Notice that (X, Z) is observed, but (U_0, U_1, V) is not. Therefore, we need some assumptions on the unobserved parameters to make the model tractable. We assume that V is a continuous random variable with a strictly increasing distribution function F_V and (U_0, U_1, V) is statistically independent of Z given X. Therefore, the decision rule can be written as:

$$D = 1(Z^{'}\gamma > V) \tag{3}$$

Let $P(Z)$ denote the probability of working formally $(D = 1)$ conditional on $Z = z$, such that $P(Z) = Pr(D = 1Z = z) = F_V(\mu_D(Z))$. We keep conditioning on X, but to make notation easier it is omitted from now on. Now define $U_P = F_V(V)$, which is uniformly distributed by construction. This transformation is useful because different values of U_P correspond to different quantiles of V. Rewriting Equation 3 using the transformation of the error term and $P(Z)$, we get:

$$D = 1(P(Z) > U_P) \tag{4}$$

Now we can rewrite Equation 3 as:

$$\begin{aligned} Y = (1-D)y_0 + DY_1 = D(\mu_1(X) + U_1) + (1-D)(\mu_0(X) + U_0) \\ = D(X^{'}\beta_1 + U_1) + (1-D)(X^{'}\beta + U_0) \\ = X^{'}\beta_0 + D(X^{'}\beta_1 - X^{\prime}\beta_0) + D(U_1 - U_0) + U_0 \end{aligned} \tag{5}$$

Assuming that $\mu_1(X)$ and $\mu_0(X)$ also have a linear representation such that $\mu_j(X) = X\beta_j$.

The conditional expectation of Y given $X = x$ and $P(Z) = p$ is:

$$\begin{aligned} E(Y|X = x, P(Z) = p) = E(Y_0|X = x, P(Z) = p) + E(Y_1 - Y_0|X = x, D = 1, P(Z) = p)p \\ = X^{'}\beta_0 + (X^{'}\beta_1 - X^{'}\beta_0)p + pE(U_1 - U_0|U_D \leq p) \end{aligned} \tag{6}$$

To estimate 6 we need to consider three cases. As Belskaya et al. (2020) state, the potential results could be: (i) if the unobserved terms are homogeneous, that is $U_0 = U_1 = \bar{U}$ for all individuals, then the last term of Equation 6 cancels out; (ii) the unobserved terms are heterogeneous but mean-independent of the formality decision, that is $E(U_1 - U_0X = x, U_D = u_D) = E(U_1 - U_0)$, then the last term of Equation 6 cancels out; and (iii) if the unobserved terms are heterogeneous and correlated with V (the error term from the selection equation), then the last term of Equation 6 cannot be ignored, because it reflects "selection on gains".

If in this framework we were going to use a classic instrumental variables approach, we would assume that individuals do not sort into formal jobs based on their expected gains of having a job of such type. This is yet to be proven because it may be the case that individuals who know they have a preference for jobs without a boss or in which they can control their time, for example, want to have informal jobs or being self-employed. This is called selection on gains: given that the returns to job type are heterogeneous across individuals, those who will benefit the most from being formal or informal are more likely to select into that type of job.

Therefore, MTE methodology does not assume that the returns of formality are the same for everyone, as it allows for accounting for selection on gains.

Following Carneiro et al. (2011), this model assumes that agents know the gross return on earnings of having each type of job. This means that individuals know $\Delta = Y_1 - Y_0 = (X^{'}\beta_1 - X^{'}\beta_0) + (U_1 - U_0)$.

In the third case analyzed before what is happening is that individuals who are identical on their set of X's may make different decisions about which type of employment to get (formal or informal), influenced by their unobserved component V in the selection equation. As a result of this feature, the returns of working formally or informally, for observationally identical individuals, will depend upon a constant component $(X^{'}\beta_1 - X'\beta_0)$ and an individual-specific component $E(U_1 - U_0|X = x, U_D = u_D)$.

$$MTE(z,p) = \frac{((Y|X = x, P(Z) = p))}{\partial p} = (X^{'}\beta_1 - X^{'}\beta_0) + E(U_1 - U_0|X = x, U_D = u_D) \quad (7)$$

The last term of Equation 7 can be estimated in a parametric version and in a semi-parametric version, both versions can be estimated using polynomials of different orders or not. For this version of the paper, I will use both parametric approaches explained below.

- Parametric estimation using Local Instrumental Variables (LIV): As Heckman and Vytlacil (2005) show, the MTE can be recovered from the derivative of the conditional expectation of Y with respect to the propensity score as Equation 7 shows. Under essential heterogeneity, as it is the selection on gains, the MTE can be identified using non-linearities in the expectation of Y given p, without further imposing a joint distribution between the selection equation and the outcomes. If the independence assumption holds and, in addition, we have that U_D is additive separable from Z as stated under Equation 3, then we can recover all the treatment parameters from the MTE using the LIV approach. The downside of this approach is that we cannot recover $(\beta_1, \beta_0, \sigma_{1V}, \sigma_{0V})$ independently, which we required to test for the segmentation versus comparative advantage hypothesis.
- Parametric estimation using maximum likelihood: Under the parametric framework, assuming a multivariate normal parameterization Equation 8 can be expressed as:

$$\begin{aligned} MTE(x, u_D) &= X^{'}(\beta_1 - \beta_0) + E(U_1 - U_0|U_D = u_D) \\ &= X^{'}(\beta_1 - \beta_O) + E(U_1 - U_0|V = \phi^{-1}(U_D)) \\ &= X^{'}(\beta_1 - \beta_0) + (\sigma_{1V} - \sigma_{0V})\phi^{-1}(U_D) \end{aligned} \quad (8)$$

The parameters $(\beta_1, \beta_0, \sigma_1 V, \sigma_0 V)$ and their standard errors can be estimated by maximum likelihood methods following Lokshin and Sajaia (2004), who specified the loglikelihood function presented in the Appendix A.3, or (ii) Following Maddala (1983), who proposes a linear regression model augmented by a binary endogenous treatment variable and assumes that $\beta_1 = \beta_0$ and $\sigma_0^2 = \sigma_1^2$. This paper follows Lokshin and Sajaia (2004) approach given that it imposes less restrictions on the model. The downside of this approach is that we are imposing a strong restriction on the joint distribution of (U_1, U_0, V) and the MTE estimation is very sensitive to functional form specification (Andersen, 2018).

Under the maximum likelihood estimation and following Magnac (1991), there are two hypotheses that can be tested. On one side, the segmented labor markets hypothesis claims that access to the formal labor market is restricted by minimum wages, tax laws, and other labor regulations, thus lower productivity workers are rationed out of the formal sector and can only find jobs in the informal sector. If true, we should observe that: $cov(U_1, V) < 0$ and $cov(U_0, V) < 0$. On the other side, the comparative advantage hypothesis says that informal jobs reflect worker's implicit choices given their preferences, skills, the cost and benefits of formality, and the availability of other means of social protection (Perry et al., 2007). If true, we should observe that: $cov(U_1, V) < 0$ and $cov(U_0, V) > 0$.

4.3. Identification

Theoretically, the parameters of interest could be identified from non-linearities in the selection equation. But as the MTE model is highly sensitive to functional form specification and we are imposing a parametric structure to the MTE model, then it is recommended to include at least one valid exclusion restriction in the selection equation 2 that add exogenous variation conditional on controls. This means that the selection equation should contain at least one variable that is not included in the outcome equation that affects the decision to be formal or informal but does not affect wage rate directly besides its effect through the decision rule (being formal or not).

Given these requirements, the data about labor inspections from the Ministry of Labor and data on state size, following what Almeida and Carneiro (2012) did, provide good exclusion restrictions based on the cost that inspectors put on potential violators and keeping in mind that there is also a technology involved in the process of inspections that depends on the cost for an inspector of going to some remote place for doing an inspection. Thus, the exclusion restrictions used are the log number of inspectors per state, the log urban area of the state in squared kilometers, and an interaction term between the number of inspectors per office at the state level and the urban area measure times 10,000.

5. Results

This section presents the results for the OLS and MTE models, and it discusses the implications of such results.

5.1. OLS and IV

OLS coefficients can be interpreted as a biased Average Treatment on the Treated (ATT), as $OLS = ATT + E[Y_0 D = 1] - E[Y_0 D = 0] = ATT + SelectionBias$. The results presented in Table 7 suggest that formal workers earn, on average, wage rates that are 12.1% higher than the wages of informal workers. In this case, we suspect of negative selection bias as the higher the unobserved cost of formality, the less likely a person is going to work formally. Other coefficients in the regression should be interpreted with caution as they could be biased. Their purpose on the model is to act as controls, not as the coefficients of interest.

We repeat the same exercise excluding all controls and using a classical instrumental variables design estimated via GMM, given that the endogenous instrumented variable, formal status, is binary. The results, reported in Table 8, confirm that the effect of formality on wage rate is biased as there is selection that needs to be addressed. This bias is reduced when modeling the decision of being formal.

Table 7: *OLS Results*

Variable	Coef/SE
Formality	0.121***
	(0.004)
Female	-0.247***
	(0.003)
Age at the time of survey	0.058***
	(0.001)
Age squared	-0.001***
	(0.000)
Married	0.037***
	(0.004)
Schooling level (Primary school or less=base)	
High school	0.201***
	(0.004)
College	0.688***
	(0.006)
Grad school	1.290***
	(0.021)
Ethnicity (white=base)	
Indigenous	-0.089***
	(0.033)
Afro-Brazilian	-0.118***
	(0.006)
Asian	0.142***
	(0.031)
Mixed	-0.099***
Urban	0.108***
	(0.007)
Log GDP Per Capita	0.161***
	(0.009)
Constant	-1.044***
	(0.093)
No. of Observations	105,197

Notes: Dependent variable: Log hourly wage rate. Robust standard errors in parentheses. Significance: ***p ¡ 0.01; **p ¡ 0.05; *p ¡ 0.1. This table shows basic OLS results for the wage equation, in which "Works formally" is included as an independent variable. Region dummies are included.

Table 8: *Additional OLS and instrumental variables results*

	OLS (1)	OLS (2)	OLS (3)	IV (1)	IV (2)	IV (3)
ATE	0.269***	0.163***	0.121***	0.229***	0.155***	0.121***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Individual level controls	No	Yes	Yes	No	Yes	Yes
State level controls	No	No	Yes	No	No	Yes
Observations	105,197	105,197	105,197	105,197	105,197	105,197

Notes: Dependent variable: Log hourly wage rate. Robust standard errors in parentheses. Significance: ***p ¡ 0.01; **p ¡ 0.05; *p ¡ 0.1. This table shows the OLS and IV GMM estimation results for the wage equation, in which "Log of wage rate" is the dependent variable. Individual level controls include gender, age, age squared, schooling level and self-declared ethnicity. State and regional controls include a dummy for urban status of the location city, state per capita GDP in 2015, and administrative regions dummy.

5.2. Marginal Treatment Effects

Based on the hypothesis presented by Magnac (1991), informality in Brazil responds to comparative advantage as workers are selecting themselves into the sector their skills are going to be better rewarded. Table A1 and Table A2 show the selection equation and wage equation that were jointly estimated to compute the marginal treatment effect model. Figure 3 shows the full distribution of the MTE over the domain of the unobserved cost of being formal (U). The graph shows the effect of formality when we compare a formal individual against an individual who is indifferent between formality and informality, given their unobserved non-pecuniary costs, U.

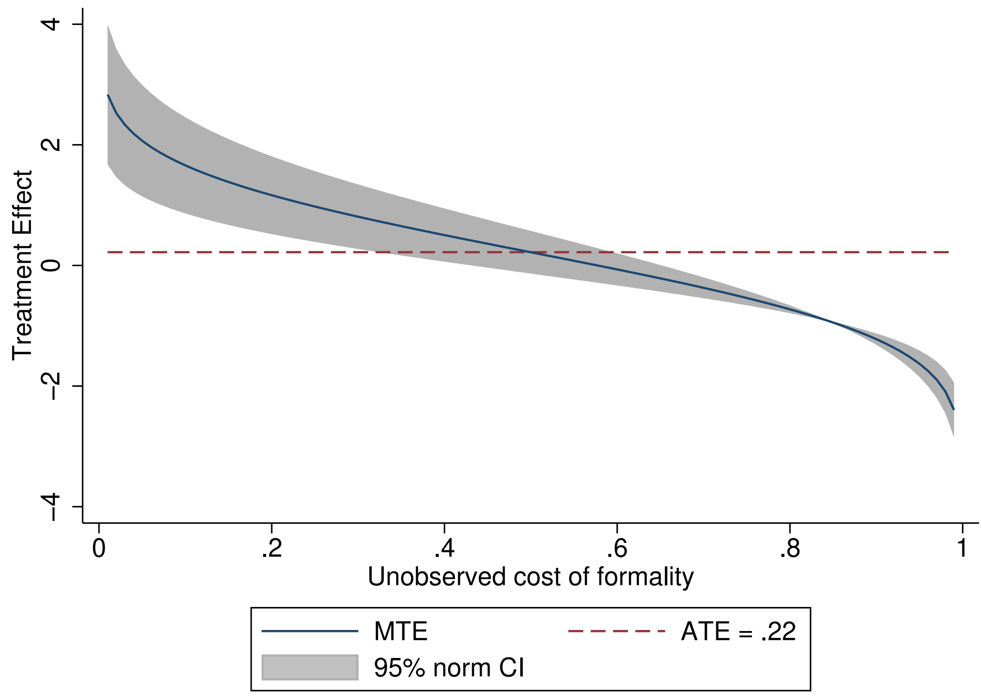
The ATE of formality is 0.219, which means that formal workers earn, on average, wage rates that are 22% higher than informal workers, but the result is not statistically different from zero. The covariances between the wage equations and the selection equation are $cov(U_1, V) = -0.6 < 0$ and $cov(U_0, V) = 0.4 > 0$, both are significant at 1%. This confirms the comparative advantage hypothesis as formal workers are the ones who have a lower cost of being formal (lower U) and informal workers are the ones who have the highest cost of being formal (higher U). Additionally, as $cov(U_1, V) - cov(U_0, V) < 0$, this means that there is selection on gains, as those with the highest gains from the treatment are the ones who are more likely to be formal.

The exclusion restrictions are highly significant. The higher the number of inspectors in the state, the higher the likelihood of being formal. The larger the urban area of a state, the more likelihood of informality as it is harder to enforce regulation. The interaction term between urban area of the state and number of inspectors captures this relationship.

6. Robustness Checks

This section includes different robustness checks that support the findings of the previous section.

Figure 3: *Marginal Treatment Effect*



Notes: Bootstrap standard errors 100 replications. This figure shows the marginal treatment effect of formality on hourly wage rate. The x-axis represents quantiles of the unobserved marginal cost of being formal. The y-axis is the treatment effect of formality on log-hourly wage rate. These are MTE estimates that come from the model specification that was reported in equation 8

6.1. Marginal Treatment Effects for Only Men

As we may have been concerned about selection into employment, especially for the female labor force, given that their participation in the labor market is significantly lower than the one by males, we estimated the same model but for a reduced sample of only men in prime age. This sample has 59,218 observations.

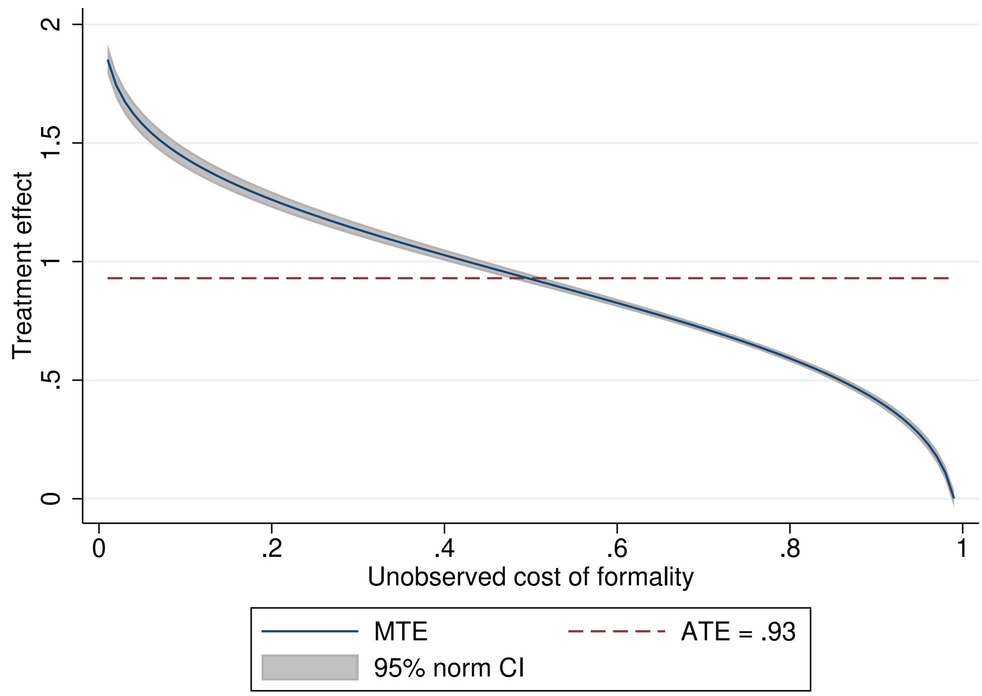
The results are included in Table A3 and Table A4. They are consistent with what we previously found that the ATE is positive but not significant. The covariances have the expected signs that support a comparative advantage hypothesis, and the slope of the MTE curve is negative.

6.2. Marginal Treatment Effect Model using a lax definition of formality: counting as formal those employees who do not have a worker's card but have CNPJ.

Under this specification, in addition to the workers we previously classified as formal under the baseline definition, we add to the formal group those employees who do not have a worker's card but have CNPJ. The results, reported in Table A5 and A6, show that there is also evidence of comparative advantage, the ATE is slightly higher than what was estimated before, but it is not significantly different from zero. The exclusion restrictions are highly significant and with the expected signs.

6.3. Marginal Treatment Effects only using individual level characteristics

Figure 4: *Marginal Treatment Effect using only individual level controls*



Notes: Bootstrap standard errors 100 replications. This figure shows the marginal treatment effect of formality on hourly wage rate. The x-axis represents quantiles of the unobserved marginal cost of being formal. The y-axis is the treatment effect of formality on log- hourly wage rate. These are MTE estimates that come from the model specification that was reported in equation 8, including only individual level characteristics.

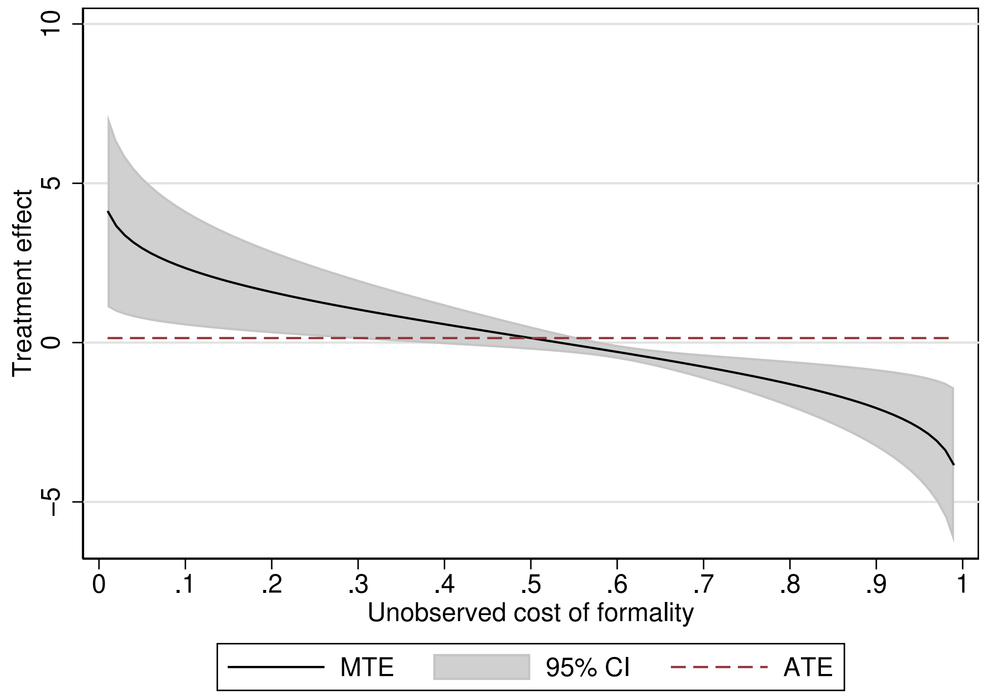
6.4. Marginal Treatment Effects using Local IV estimation method

Given the concerns that might arise as the MTE estimation method is highly sensitive to functional form, we also perform a robustness check estimating the MTE via local instrumental variables (local IV) (Table A9 and Table A10). Although this estimation method is still parametric, as it requires to have a defined functional form for the selection equation, which in this case it follows a normal distribution, it relaxes the assumption of joint normality as this condition is not necessary for identification.

The MTE results under the local IV method are similar to the ones found using maximum likelihood estimation. The recovered ATE under this approach is 0.14 and it is not statistically significant. There are small changes in the coefficients in the selection equation, but the overall ATE and MTE parameters do not differ from one another (Figure 5).

Although we cannot evaluate the comparative advantage versus segmentation hypothesis using this estimation method, due to its limitations recovering all the parameters of interest, we still find evidence of selection on gains into formality due to essential heterogeneity among workers, which explains why some workers have a lower unobserved cost of formality and get more benefits from it even though the observed characteristics to the econometrician are identical.

Figure 5: *Marginal Treatment Effect under LIV estimation method*



Notes: Bootstrap standard errors 100 replications. This figure shows the marginal treatment effect of formality on hourly wage rate. The x-axis represents quantiles of the unobserved marginal cost of being formal. The y-axis is the treatment effect of formality on log-hourly wage rate. These are MTE estimates that come from the model specification that was reported in equation 7, estimated using Local IV.

7. Policy Experiments

The MTE framework allows us to evaluate different policy experiments. In this regard, Heckman and Vytlacil (2005) developed the Policy Relevant Treatment Effect (PRTE) parameter, which is defined as it follows:

Consider a class of policies that affect P, the probability of participating in the treatment, but do not affect the potential outcomes or unobservables related to the selection process. Let D^* be the selection choice that would be made after the policy change. Let P^* be the corresponding probability that $D^* = 1$ after the policy change. D^* is defined by $D^* = 1(P^* \geq U)$. Let $Y^* = (1 - D^*)Y_0 + D^*Y_1$ be the outcome under the alternative policy. Therefore, the mean effect of going from a baseline policy to an alternative policy per net person shifted is the PRTE, defined when $E(D) \neq E(D^*)$ as:

$$\frac{E(Y Alternative \quad policy) - E(D|baseline \quad policy)}{E(Y Alternative \quad policy) - E(D|baseline \quad policy)} = \frac{E(Y^*) - E(Y)}{E(D^*) - E(D)} \tag{9}$$

Equation 9 can be represented using the MTE already computed for each individual. Thus, it be-comes:

$$= \frac{E(Y^*) - E(Y)}{E(D^*) - E(D)} = \int_0^1 MTE(u)\omega_{PRTE}(U)du \quad (10)$$

where ω_{PRTE} are the weights given by the density function of U_D in the population of interest.[3]

Using the previously explained framework, the trivial policy to evaluate under our current specification is a policy that changes labor law enforcement through increasing the number of labor inspectors at the state level. Thus, for estimating the PRTE, we would estimate the decision probit and predict the probability of being formal for each individual under the new inspectors' policies. Then, we would estimate the PRTE using the individuals who switch decisions after the change in policy.

We propose two alternative policies to be evaluated: Policy A, which proposes to double the number of labor inspectors in the states of Minas Gerais, Rio de Janeiro and Sao Paulo, as these states comprise a large fraction of the GDP of the country and Policy B, which aims to increase the number of labor inspectors in every state of the country until reaching 5 inspectors per each 10.000 inhabitants per state. Under this second policy, the state of Sao Paulo would move from having 2.5 inspectors per 10.000 state inhabitants to 5 inspectors per 10.000 inhabitants.

Both policies increase the predicted probability of being formal, as one would expect given that know there is a higher chance of being caught in informality, but as Table A11 shows, the Policy Relevant Treatment Effect (PRTE), which is the parameter of interest under this scenario, is negative in both cases. This means that individuals who are now indifferent between being informal and formal under the alternative policies of increasing labor enforcement have, on average, wage rates that are 65% under policy A and 82% under policy B lower when becoming formal versus when they work informally.

The negative and statistically significant results are reflecting the fact that an increased number of inspectors do make some previously informal workers to switch to formality, but as the switchers have a higher unobserved cost of being formal, then the net benefits of formality are now lower, on average, than the previously estimated ATE.

This result highlights the importance of defining what the main goal of formalization policies is. If the idea behind increasing enforcement is to benefit workers as formality is assumed to be better for everyone, then more inspections are making worse-off in terms of their wage rate the workers who have a high unobserved cost of being formal.

The methodological design used in this paper does not allow us to speak about general welfare effects, but Ulyssea (2018), using a general equilibrium model, finds for Brazil that increasing enforcement through labor inspections do not necessarily make workers and firms better off at the same time. In a similar context, for Mexico, Samaniego de la Parra and Fernández Bujanda (2020) find that increasing the number of random labor inspections leads to lower formal employment, lower formal job creation, and a temporary increase of formal and informal job destruction, given that for informal workers, inspections have two effects: they increase the probability of being formalized at the inspected firm, but

[3] See Heckman and Vytlacil (2005) for a detailed explanation of how to recover all the treatment parameters from the MTE and the different weight functions used in each case

also increase the probability of dissolving the informal match.

8. Conclusion

This paper estimates the heterogeneous returns of labor informality using household survey data for Brazil and a unique dataset on labor enforcement, which includes information about number of labor inspectors in 2015, number of labor inspection offices in 2015, and other regional characteristics of the state that may affect enforcement, as an identification strategy that captures the cost of labor enforcement for Brazil. The results indicate that the higher the number of labor inspectors in a state, the higher the likelihood of individuals being formal, but being in a state with a larger urban area decreases the likelihood of being formal as inspectors now have to drive further distances and spend more time in each inspection so they can perform less inspections per inspector.

Regarding the effect on wages, workers self-select into the job type in which their skills are going to be better rewarded (formal or informal jobs). On average, the ATE of formality on wage rate is 22%, but statistically not different from zero, which implies that formal workers do not earn, on average, a premium from formality. But there are significant heterogeneous effects as workers with lower unobserved costs associated to formality do earn very high premiums of more than 100%. Opposite results are found for workers with a very high unobserved cost of being formal, given that they would get hurt if they switch to formality as their skills are better rewarded in informal jobs. Therefore, informality in Brazil seems to respond to comparative advantage.

The results found support that informality in Brazil responds to a comparative advantage hypothesis, meaning that workers self-select into the sector in which their skills are going to be better rewarded rather than being rationed out of the formal market.

The analysis of two policy experiments that aim to increase the number of labor inspectors in Brazil show that this policy is effective in inducing some individuals to move out of informality to formality, but that does not necessarily translate into better wage rates for said workers. On average, the effect of formality on wages for switchers under more stringent enforcement policies is negative, which is expected as these individuals face a higher unobserved cost of formality than the ones who already were formal under the baseline enforcement policy.

These results open the discussion about the importance of designing well rounded labor policies as if the goal with formalization policies is to increase welfare of workers by helping them to have higher wages, then it is not clear that such goal is achieved by increasing labor enforcement. Formality might bring other benefits from the social security standpoint, such as access to a retirement pension if the worker contributes for a certain amount of time but doing an analysis that takes into consideration not only general equilibrium effects of increased formality, but the time horizon cost and benefits of formality is out of the scope of this paper.

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A. Appendix

A.1. Tables and Figures

Table A1: *Selection Equation: Probit model*

Variables	Coef./SE
Female	-0.212***
	(0.008)
Age at the time of survey	0.057***
	(0.003)
Age squared	-0.001***
	(0.000)
Married	0.113***
	(0.008)
Schooling level (Primary school or less=base)	
High school	0.450***
	(0.009)
College	0.744***
	(0.012)
Graduate school	0.905***
	(0.044)
Ethnicity (white=base)	
Indigenous	-0.124*
	(0.068)
Afro-Brazilian	-0.125***
	(0.013)
Asian	0.224***
	(0.063)
Mixed	-0.113***
	(0.009)
Urban	0.332***
	(0.016)
Log number of state inspectors	0.076***
	(0.011)
Log state urban area in sq. km	-0.062***
	(0.010)
Interaction	-0.000
	(0.001)
Constant	-1.148***
	(0.070)
Number of observations	105,197

Notes: Dependent variable: Works formally (=1). Robust standard errors in parentheses. Significance: ***p ¡ 0.01; **p ¡ 0.05; *p ¡ 0.1. This table shows the probit model for the decision of being formal, in which "Works formally" is the dependent variable. Region dummies are included.

Table A2: *Wage equation*

Variables	Treated [D=1]	Untreated [D=0]
Female	-0.302***	-0.151***
	(0.005)	(0.007)
Age at the time of survey	0.065***	0.040***
	(0.002)	(0.002)
Age squared	-0.001***	-0.000***
	(0.000)	(0.000)
Married	0.079***	-0.008
	(0.005)	(0.007)
Schooling level (Primary school or less=base)		
High school	0.353***	0.048***
	(0.006)	(0.010)
College	0.827***	0.405***
	(0.007)	(0.015)
Graduate school	1.465***	0.884***
	(0.024)	(0.046)
Ethnicity (white=base)		
Indigenous	-0.122***	-0.065
	(0.044)	(0.056)
Afro-Brazilian	-0.148***	-0.047***
	(0.008)	(0.012)
Asian	0.162***	0.097
	(0.035)	(0.064)
Mixed	-0.123***	-0.053***
	(0.005)	(0.008)
Urban	0.213***	0.033***
	(0.011)	(0.013)
Log GDP Per Capita	0.156***	0.155***
	(0.008)	(0.016)
Constant	-1.480***	-0.953***
	(0.095)	(0.173)
Sigma	-0.641***	0.483***
	(0.003)	(0.018)
Sigma1v – Sigma0v	-1.124***	
	(0.019)	
ATE	0.219	
	(0.204)	
Number of observations	105,197	

Notes: Dependent variable: log hourly wage rate. Bootstrap standard errors 100 replications. Significance: ***p ¡ 0.01; **p ¡ 0.05; *p ¡ 0.1. This table shows the maximum likelihood estimation regression results for the outcome equation. Region dummies are included.

Table A3: *Selection equation for model including only men*

Variables	Coef./SE
Age at the time of survey	0.064***
	(0.004)
Age squared	-0.001***
	(0.000)
Married	0.149***
	(0.011)
Schooling level (Primary school or less=base)	
High school	0.464***
	(0.012)
College	0.707***
	(0.016)
Graduate school	0.823***
	(0.066)
Ethnicity (white=base)	
Indigenous	-0.071
	(0.091)
Afro-Brazilian	-0.105***
	(0.018)
Asian	0.185**
	(0.087)
Mixed	-0.086***
	(0.012)
Urban	0.278***
	(0.021)
Log number of state inspectors	0.094***
	(0.015)
Log state urban area in sq. km	-0.072***
	(0.013)
Interaction	-0.001
	(0.001)
Constant	-1.302***
	(0.093)
Number of observations	59,218

Notes: Notes: Dependent variable: Works formally (=1). Robust standard errors in parentheses. Significance: ***p ¡ 0.01; **p ¡ 0.05; *p ¡ 0.1. This table shows the probit model for the decision of being formal, in which "Works formally" is the dependent variable. Region dummies are included.

Table A4: *Wage equation for model including only men*

Variables	Treated [D=1]	Untreated [D=0]
Age at the time of survey	0.076***	0.034***
	(0.002)	(0.003)
Age squared	-0.001***	-0.000***
	(0.000)	(0.000)
Married	0.098***	-0.016
	(0.007)	(0.010)
Schooling level (Primary school or less=base)		
High school	0.359***	0.043***
	(0.008)	(0.012)
College	0.819***	0.344***
	(0.010)	(0.019)
Graduate school	1.432***	0.835***
	(0.035)	(0.067)
Ethnicity (white=base)		
Indigenous	-0.133**	-0.019
	(0.059)	(0.076)
Afro-Brazilian	-0.139***	-0.065***
	(0.011)	(0.016)
Asian	0.142***	0.055
	(0.048)	(0.089)
Mixed	-0.109***	-0.062***
	(0.007)	(0.011)
Urban	0.186***	0.028*
	(0.014)	(0.016)
Log GDP Per Capita	0.145***	0.122***
	(0.012)	(0.022)
Constant	-1.604***	-0.507**
	(0.131)	(0.235)
Sigma	-0.640***	0.521***
	(0.004)	(0.021)
Sigma1v – Sigma0v	-1.161***	
	(0.021)	
ATE	0.305	
	(0.232)	
Number of observations	59,218	

Notes: Dependent variable: Log hourly wage rate. Bootstrap standard errors 100 replications. Significance: ***p ¡ 0.01; **p ¡ 0.05; *p ¡ 0.1. This table shows the maximum likelihood estimation results for the outcome equation. Region dummies are included.

Table A5: *Selection equation using a lax definition of formality*

Variables	Coef./SE
Dep. Var: Being formal	
Female	-0.228***
	(0.008)
Age at the time of survey	0.032***
	(0.003)
Age squared	-0.000***
	(0.000)
Married	0.105***
	(0.008)
Schooling level (Primary school or less=base)	
High school	0.455***
	(0.009)
College	0.793***
	(0.012)
Graduate school	0.926***
	(0.047)
Ethnicity (white=base)	
Indigenous	-0.149**
	(0.069)
Afro-Brazilian	-0.144***
	(0.014)
Asian	0.201***
	(0.067)
Mixed	-0.131***
	(0.009)
Urban	0.358***
	(0.016)
Log number of state inspectors	0.104***
	(0.012)
Log state urban area in sq. km	-0.076***
	(0.010)
Interaction	0.000
	(0.001)
Constant	-0.522***
	(0.074)
Number of observations	105,197

Notes: Dependent variable: Works formally (=1). Robust standard errors in parentheses. Significance: ***p ¡ 0.01; **p ¡ 0.05; *p ¡ 0.1. This table shows the probit model for the decision of being formal, in which “Works formally” is the dependent variable. Region dummies are included.

Table A6: *Wage equation using lax definition of formality*

Variables	Treated [D=1]	Untreated [D=0]
Female	-0.306***	-0.143***
	(-0.005)	(-0.008)
Age at the time of survey	0.059***	0.046***
	(-0.002)	(-0.003)
Age squared	-0.001***	-0.000***
	(0.000)	(0.000)
Married=1	0.071***	-0.001
	(-0.005)	(-0.008)
Schooling level (Primary school or less=base)		
High school	0.341***	0.044***
	(0.005)	(0.011)
College	0.833***	0.407***
	(0.007)	(0.019)
Grad school	1.477***	0.837***
	(0.023)	(0.053)
Ethnicity (white=base)		
Indigenous	-0.125***	-0.050
	(0.042)	(0.060)
Afro-Brazilian	-0.150***	-0.040***
	(0.008)	(0.013)
Asian	0.169***	0.059
	(0.033)	(0.072)
Mixed	-0.126***	-0.049***
	(0.005)	(0.009)
Urban	0.210***	0.027*
	(0.010)	(0.014)
Log GDP Per Capita	0.165***	0.142***
	(0.008)	(0.018)
Constant	-1.470***	-1.002***
	(0.093)	(0.172)
Sigma	-0.593***	0.479***
	(0.003)	(0.024)
Sigma1v – Sigma0v	-1.071***	
	(0.024)	
ATE	0.323	
	(0.284)	
Number of observations	105,197	

Notes: Dependent variable: Log hourly wage rate. Bootstrap standard errors 100 replications. Significance: ***p ¡ 0.01; **p ¡ 0.05; *p ¡ 0.1. This table shows the maximum likelihood estimation results for the outcome equation. Region dummies are included.

Table A7: *Selection equation for MTE only including individual level controls*

Variables	Coef./SE
Female	-0.161***
	(0.008)
Age at the time of survey	0.035***
	(0.003)
Age squared	-0.001***
	(0.000)
Married	0.103***
	(0.008)
Schooling level (Primary school or less=base)	
High school=1	0.436***
	(0.009)
College	0.522***
	(0.012)
Grad school=1	0.600***
	(0.046)
Ethnicity (white=base)	
Indigenous	-0.098
	(0.071)
Afro-Brazilian	-0.034**
	(0.014)
Asian	0.124*
	(0.068)
Mixed	-0.052***
	(0.009)
Urban	0.353***
	(0.015)
Log number of state inspectors	0.110***
	(0.014)
Log state urban area in sq. km	-0.087***
	(0.012)
Interaction	0.008***
	(0.001)
Constant	-0.920***
	(0.081)
Number of observations	105,197

Notes: Dependent variable: Works formally (=1). Robust standard errors in parentheses. Significance: ***p ¡ 0.01; **p ¡ 0.05; *p ¡ 0.1. This table shows the probit model for the decision of being formal, in which "Works formally" is the dependent variable. Region dummies are included.

Table A8: *Wage equation for MTE only including individual level controls*

Variables	Treated [D=1]	Untreated [D=0]
Female	-0.241***	-0.153***
	(0.004)	(0.007)
Age at the time of survey	0.052***	0.044***
	(0.001)	(0.003)
Age squared	-0.000***	-0.000***
	(0.000)	(0.000)
Married	0.032***	-0.017**
	(0.004)	(0.007)
Schooling level (Primary school or less=base)		
High school=1	0.145***	0.006
	(0.005)	(0.009)
College	0.640***	0.421***
	(0.006)	(0.012)
Grad school=1	1.256***	0.934***
	(0.020)	(0.046)
Ethnicity (white=base)		
Indigenous	-0.102**	-0.066
	(0.040)	(0.060)
Afro-Brazilian	-0.169***	-0.094***
	(0.007)	(0.012)
Asian	0.127***	0.135**
	(0.030)	(0.067)
Mixed	-0.132***	-0.077***
	(0.005)	(0.008)
Constant	1.073***	0.373***
	(0.029)	(0.048)
Sigma	0.235***	0.633***
	(0.007)	(0.009)
Sigma1v – Sigma0v	-0.398***	
	(0.011)	
ATE	0.926***	
	(0.010)	
Number of observations	105,197	105,197

Notes: Dependent variable: log hourly wage rate. Bootstrap standard errors 100 replications. This table shows the maximum likelihood estimation results for the outcome equation. Only individual level variables are included.

Table A9: *Selection equation using Local IV estimation method*

Variables	Coef./SE
Female	-0.157***
	(0.008)
Age at the time of survey	0.035***
	(0.003)
Age squared	-0.001***
	(0.000)
Married	0.110***
	(0.008)
Schooling level (Primary school or less=base)	
High school	0.451***
	(0.009)
College	0.535***
	(0.012)
Grad school	0.610***
	(0.046)
Ethnicity (white=base)	
Indigenous	-0.091
	(0.072)
Afro-Brazilian	-0.063***
	(0.014)
Asian	0.134***
	(0.068)
Mixed	-0.075***
	(0.009)
Urban	0.353***
	(0.017)
Log number of state inspectors	0.162***
	(0.016)
Log state urban area in sq. km	-0.099***
	(0.014)
Interaction	0.005***
	(0.012)
Constant	-1.081***
	(0.088)
Number of observations	105,197

Notes: Dependent variable: Works formally (=1). Robust standard errors in parentheses. Significance: ***p ¡ 0.01; **p ¡ 0.05; *p ¡ 0.1. This table shows the probit model for the decision of being formal, in which "Works formally" is the dependent variable. Region dummies are included.

Table A10: *Wage equation using Local IV estimation method*

Variables	Beta0	Beta1 – Beta0
Female	-0.030***	-0.117***
	(0.025)	(0.049)
Age at the time of survey	-0.033***	0.152***
	(0.007)	(0.012)
Age squared	0.000***	-0.002***
	(0.000)	(0.000)
Married	0.003	0.084***
	(0.024)	(0.039)
Schooling level (Primary school or less=base)		
High school	0.077	0.325***
	(0.084)	(0.143)
College	0.520***	0.420***
	(0.102)	(0.169)
Grad school	1.045***	0.530***
	(0.197)	(0.281)
Ethnicity (white=base)		
Indigenous	0.014	-0.159
	(0.111)	(0.196)
Afro-Brazilian	0.178***	-0.499***
	(0.030)	(0.049)
Asian	0.169	0.005
	(0.182)	(0.239)
Mixed	0.071***	-0.295***
	(0.023)	(0.038)
Urban	-0.082	0.300***
	(0.052)	(0.114)
Constant	2.647***	-3.032***
	(0.169)	(0.240)
Mills Ratio	-1.715***	
	(0.595)	
ATE	0.142	
	(0.185)	
Number of observations	105,197	

Notes: Dependent variable: log hourly wage rate. Significance: ***p ¡ 0.01; **p ¡ 0.05; *p ¡ 0.1. Bootstrap standard errors 100 replications. This table shows the maximum likelihood estimation results for the outcome equation. Region dummies are included.

Table A11: *Policy Relevant Treatment Effect*

	Baseline (2017)	Policy A	Policy B
ATE	0.219		
PRTE		-0.654***	-0.826***
Number of Inspectors per state			
Acre	18	18	402
Alagoas	37	37	1,670
Amapa	16	16	383
Amazonas	46	46	1,969
Bahia	133	133	7,602
Brasilia	56	56	1,457
Ceara	102	102	4,452
Espirito Santo	82	82	1,965
Goias	69	69	3,305
Maranhao	40	40	3,452
Mato Grosso	60	60	1633
Mato Grosso do Sul	42	42	1,326
Minas Gerais	263	500	10,435
Para	77	77	4,088
Paraiba	44	44	1,986
Parana	116	116	5,582
Pernambuco	105	105	4,673
Piaui	56	56	1,602
Redonia	34	34	884
Rio Grande do Norte	50	50	1,721
Rio Grande do Sul	184	184	5,624
Rio de Janeiro	232	500	8,275
Roraima	13	13	253
Santa Catarina	91	91	3,410
Sao Paulo	435	1,000	22,198
Sergipe	38	38	1,121
Tocantins	27	27	758
Total	2,466	3,536	102,226

Notes: Dependent variable: Log hourly wage rate. Significance: ***p ¡ 0.01; **p ¡ 0.05; *p ¡ 0.1. This table shows the PRTE estimate for two alternative policies evaluated using the MTE framework. The selection equation estimated under both alternative policies was identical to the baseline scenario, only changing the number of labor inspectors as proposed in each policy. The results were obtained using the Stata command “mtefe”.

A.2. Definitions and description of variables

Notes:

1. Political and administrative division of Brazil:

    - Regions: There are 5 administrative regions in Brazil created by the Brazilian Institute of Geography and Statistics. The regions are: North, Northeast, Central-West, Southeast and South region. States in each region share economic and geographic characteristics. See

Figure 6 for details.

- Federative Units: There are 27 federative units in Brazil: One Federal District, where the administrative capital of the country is located, and 26 states. This unit is equivalent to a state in the United States. For the purpose of this work, all the federative units are going to be called “states”.
- Municipalities: Each state is divided in municipalities. There are over 5,500 municipalities in the country. In this paper, municipalities are not used.

2. Formal/informal status only considers individuals’ main jobs. Main job is defined in the survey as the the job the person spent most of her time during the previous 365 days.

Figure 6: *Regions of Brazil*

Description of Variables*

Variable	Notes
Hourly wage rate (log)	=ln(Labor earnings per month at main job / Weekly hours of work * 4.33) Labor earnings per month are defined as follows: • Monthly average (over the last 12 months) after-tax real labor earnings from main job in 2015 • Real earnings are computed using average CPI from 2015 as the base year. • Labor earnings do not include payments in kind or other benefits. Hours of work per week are defined as follows: – Usual hours worked per week for 2015 Hours of work per week are defined as follows:
Formal (binary)	=1 if the respondent has a signed workers card or if the respondent has an official registration (CNPJ) of her entrepreneurial activity or free-lance activity. =0 if individual does not have a signed workers card or does not have a CNPJ Note: In order to classify the job of a worker, the respondent has to answer the following question "In your job you work as: [5 options are displayed]" The options are: employee, domestic worker, self-employed, entrepreneur with at least one employee, non-salaried worker, construction worker working for myself state farm, farming industry, store, army, government service, or other.

A.3. Log-likelihood function under joint normality assumption

Under the potential outcomes framework defined by equation 1 and the selection equation 2, the switching regression model assumes that the error terms of the three equations follow a multivariate normal distribution, such as $(U_0, U_1, V) \sim N(0,)$, and (U_0, U_1, V) is independent from (X, Z). The variance of V is normalized to 1, such that $\sigma_V^2 = 1$, and the covariance between U_0 and U_1 cannot be recovered given that we never observe both outcomes simultaneously. Therefore σ_{10} is not identified. The variance-covariance matrix in this case is:

Cont. Description of Variables

Variable	Notes
Female (binary)	• =1 if the respondent is female • =0 if male
Age, Age squared Age at the time of the survey	
Married (binary)	• =1 if the respondent is married or living together, • =0 if has never been married, divorced, or widowed.
Ethnicity (categorical)	Respondent's self-declared ethnicity: • =1 if white (excluded category) • =2 if Afro-Brazilian • =3 if Asian • =4 if indigenous • =5 if mixed
Urban Status (binary)	Respondent lives in: • =1 if urban • =0 if rural

$$\begin{pmatrix} \sigma_0^2 & \sigma_{10} & \sigma_{0V} \\ \sigma_{10} & \sigma_1^2 & \sigma_{1V} \\ \sigma_{0V} & \sigma_{1V} & 1 \end{pmatrix}$$

Following Lokshin and Sajaia (2004), the model can be efficiently estimated by using the full-information Maximum Likelihood method to jointly estimate both the outcome equation and the decision rule. The loglikelihood function of the model in this case would be:

$$ln(L) = \sum_i D\omega_1[ln(F(\eta_{1i})) + ln\left(\frac{f(\frac{U_1}{\sigma_1})}{\sigma_1}\right)] + (1-D)\omega[ln(1-F(\eta_{0i})) + ln\left\{\frac{f(\frac{U_0}{\sigma_0})}{\sigma_0}\right\}]) \quad (11)$$

Where:

- F: Cumulative normal distribution

- f: Normal density distribution
- ω_i: Optional weighting for observation i
- $\eta ji = \frac{Z_\gamma + \rho_j(\frac{U_j}{\sigma_j})}{\sqrt{1-\rho_j^2}}$ for j=0,1 and $\rho_j = \frac{\sigma_j^2 v}{\sigma_v \sigma_j}$ are the correlation coefficients.

In order to estimate 7, we need a transformation of the correlation coefficients and standard deviations to guarantee that the correlation is between -1 and 1 and the standard deviation is always positive. This is done in a way that it is easy to recover the true parameters of the model. For the case of the standard deviations, $ln(\sigma_j)$ is used instead of using σ_j. For the correlations, the Fischer's transformation is the standard: $atanh(\rho_j) = \frac{1}{2}(\frac{(1+\rho_j)}{(1-\rho_j)})$.

Cont. Description of Variables

Variable	Notes
Regions (categorical)	Large regions of Brazil: • =1 if North • =2 if Northeast • =3 Center-West • =4 Southeast (excluded category) • =5 South
GDP per capita	GDP per capita is measured as follows: • State GDP is deflated by using the CPI then each state GDP is divided by the size of the state population at that year GDP *source: Brazilian Institute of Geography and Statistics* CPI *source: Fundacao Getulio Vargas* Population *source: Brazilian Institute of Geography and Statistics*
Inspectors per state	=ln(inspectors per state) *Source: Ministry of Labor and Employment* =ln (No. inspectors / No. offices)
Ratio inspectors per inspection office	Number of inspectors is defined at the state level. Number of inspection offices is defined at the state level *Source: Ministry of Labor and Employment*
Urban area of the state	=ln(urban area of the state in sq. km) *Source: Instituto Brasileiro de Geografia e Estatistica*

=1 if the respondent has a signed workers card or if the respondent has an official registration (CNPJ) of her entrepreneurial activity or free-lance activity. =0 if individual does not have a signed workers card or does not have a CNPJ Note: In order to classify the job of a worker, the respondent has to answer the following question "In your job you work as: [5 options are displayed]" The options are: employee, domestic worker, self-employed, entrepreneur with at least one employee, non-salaried worker, construction worker working for myself state farm, farming industry, store, army, government service, or other.