Employment and Welfare Effects of the Quota for Disabled Workers in Brazil

Gustavo de Souza

REVISED
March 30, 2025

WP 2023-11

https://doi.org/10.21033/wp-2023-11

Federal Reserve Bank *of* Chicago

Employment and Welfare Effects of the Quota for Disabled Workers in Brazil

Gustavo de Souza*

Federal Reserve Bank of Chicago

This draft: March 30, 2025

First draft: October 11, 2020

Abstract

I study the effect of a quota for disabled workers on the labor market and welfare. In Brazil, firms with more than 100 workers must have between 1% and 5% of their labor force composed of disabled workers. I show that the enforcement of the quota led to a decrease in firm size and wages, despite increasing the hiring of disabled workers. At the market level, the quota increased wages and the labor force participation of disabled workers but at the cost of reduced employment for non-disabled workers. Using a model calibrated to the empirical estimates, I find that the quota for disabled workers decreased utilitarian welfare by 0.026%.

Key Words: size-dependent policy, labor market regulation, firm responses.

JEL Codes: E6, H2, H5

*This paper was part of my thesis defense and circulated under the title "The Fiscal Consequences of Active Labour Market Policies: the Case of Quota for Disabled Workers" in 2021. I dedicate this paper to my father, Geraldo Joaquim de Souza, who first opened my eyes to the challenges faced by people with disabilities and introduced me to this policy. I am greatly indebted to my thesis committee, Greg Kaplan, Robert Shimer, Mikhail Golosov, and Rodrigo Adão. This paper also benefited from valuable comments from Santiago Caicedo, Corina Mommaerts, Manasi Deshpande, Magne Mogstad, Fernando Alvarez, Mitch Downey, Joshua Weiss, Kieran Larkin, John Grigsby, Christian Moser, Thibaut Lamadon, Nicola Limodio, Cynthia Kinnan, Gina Li, as well as seminar participants in the University of Chicago's Small Macro Group (2020), Public/Labor Group (2020), IIES (2022), IIPF Annual Conference (2022), Chicago Fed (2023), Micro and Macro Perspectives of the Labor Market (2023), WEFIDEV (2024), and System Committee on Applied Microeconomics (2024). The views expressed herein are solely those of the author and do not necessarily reflect the views of the Federal Reserve Bank of Chicago or the Federal Reserve System. All remaining errors are mine. Contact: gustavo@microtomacro.net

1 Introduction

The rising cost of disability insurance has become a pressing issue in many countries. To address this challenge and promote workforce inclusion, many governments have introduced quotas requiring large firms to hire disabled workers.[1] These policies aim to expand employment opportunities for disabled individuals and reduce reliance on government disability benefits. However, because these quotas are implemented as size-dependent mandates, they may distort firm behavior, reduce productivity, and impose disproportionate costs on high-productivity firms (Caicedo et al. 2022, Amirapu and Gechter 2020, Almunia and Lopez-Rodriguez 2018). This paper studies the trade-off between the social benefits of inclusion for disabled workers and the economic distortions introduced by size-dependent hiring requirements. How do firms adjust to these quotas? What are the broader consequences for employment, firm dynamics, and welfare?

In this paper, I study the effect of the quota for disabled workers in Brazil, a policy that imposes particularly demanding hiring requirements on large firms. Brazilian firms with more than 100 workers are required to have between 1% and 5% of their workforce composed of disabled workers, with the requirement increasing discontinuously with firm size. If fully enforced without behavioral responses, the quota would raise the labor force participation of disabled workers by 70% —from 25 percentage points to 43 percentage points. In 11% of Brazilian microregions, however, the number of disabled workers needed to satisfy the quota surpasses the total number of disabled workers in the local labor market, making compliance difficult for many firms.[2]

Due to these high requirements, firms often struggle to find enough disabled workers to meet their hiring obligations. One case that illustrates these challenges is that of the newspaper "*Estado de Minas*". After failing an inspection of the quota in 2014 and facing a potential fine of R$102,000 (approximately US$31,182), the company's HR manager explained, "Half of Brazilian companies do not comply with the quota because they are unable

[1] Korea, Japan, Italy, France, Germany, Spain, Poland, Austria, Hungary, the UK, and China are examples of countries with quotas for disabled workers. In all these countries, the quota is size-dependent.

[2] A microregion is a group of economically and socially integrated municipalities, as defined by the Brazilian Institute of Geography and Statistics (IBGE). It is the Brazilian equivalent of a commuting zone in the United States.

to do so. There are no disabled individuals available for us to hire. The ones we do hire leave as soon as they get a hundred Reais more in salary from another company. Our interest is to comply with the quota; it always has been. We have even partnered with specialized organizations for this purpose, and yet we still haven't succeeded" (Transite 2016). Following the inspection, "*Estado de Minas*" reduced its workforce, which also lowered the number of disabled workers it was required to hire under the quota. Since then, the firm has passed all subsequent quota inspections.[3]

In this paper, I use microdata and a structural model to show that firms respond to the quota for disabled workers, a size-dependent policy, by downsizing. After an inspection, firms near a quota discontinuity reduce their workforce, meeting the requirement through contraction and increased hiring of disabled workers. At the market level, the quota increased wages and the labor force participation of disabled workers, but at the cost of reduced employment for non-disabled workers. Using a model calibrated to match the empirical elasticities, I estimate that the quota reduced output and utilitarian welfare by 0.27% and 0.026%, respectively. In contrast, I show that subsidizing the hiring of disabled workers is a strictly better policy, increasing utilitarian welfare by 0.034%. A subsidy leads to a more efficient allocation of labor because it allows disabled workers to sort into sectors where they are relatively more productive, since—unlike a quota—a subsidy does not impose uniform hiring requirements across all firms.

To study the effect of the quota on firms, I merge an administrative matched employer–employee dataset on disabled and non-disabled workers with the complete record of quota inspections carried out by the Division of Equal Opportunity (DEO) of the Ministry of Labor in Brazil, which has the sole purpose of enforcing the quota for disabled workers. Prior to an inspection, most firms are either unaware of the quota or have decided not to comply with it. The DEO does not immediately impose fines or enforce other labor regulations; instead, it nudges firms toward compliance by informing them of their obligations and granting them 90 days to meet the quota before penalties take effect.

[3] After failing the inspection, "*Estado de Minas*" appealed to higher courts, arguing that there are not enough disabled workers in the labor market. This challenge is not a one-off occurrence—many firms have formally appealed to have their quota requirement reduced or lifted, citing the lack of available disabled workers in the market. Tribunal Regional do Trabalho da 3ª Região (2022), Vermelho (2018), and Migalhas (2025) are a few prominent cases.

I use DEO inspections to identify the effect of the quota for disabled workers on firms. Because these inspections are carried out solely to inform firms about the quota and encourage compliance—without enforcing other labor regulations—they effectively represent a sudden implementation of the quota. I implement a matched event study, comparing firms inspected today to otherwise similar firms inspected in the future. The identifying assumption is that the timing of inspections is uncorrelated with firm-level shocks.

I provide empirical and institutional evidence supporting the assumption that the timing of inspections is as good as random. Specifically, I show that, conditional on being inspected, neither firm characteristics nor growth rates predict the year of inspection or the probability that a firm will be inspected in the future. Additionally, I demonstrate that inspections of the quota for disabled workers do not correlate with other government interventions, such as campaign contributions, public procurement, or subsidized loans. Furthermore, I find that inspections do not correlate with other labor market infractions, which is expected because the DEO enforces only the quota for disabled workers. Finally, I show that pre-period parallel trends hold for all variables of interest.

Enforcement of the quota for disabled workers decreased overall employment and wages, despite increasing the hiring of disabled workers. Inspected firms hired 20% more disabled workers in two years, increasing their likelihood of satisfying the quota by 14%. However, the firms' total workforce decreased by 3%, driven by a 4% reduction in the employment of non-disabled workers.

The negative effect of the quota on firm size is concentrated among firms located just above the policy's discontinuity thresholds, consistent with firms strategically downsizing to reduce their quota obligations. Inspections reduce firm size only among firms near a threshold, while firms farther away do not exhibit significant changes in employment. I estimate that 58% of firms that meet the quota following an inspection do so only because they shrink enough to lower the number of disabled workers they are required to hire. This response is particularly pronounced in sectors where accommodating disabled workers is more challenging—such as agriculture—indicating that firms are more likely to downsize when compliance costs are high. While firms do not bunch at the quota discontinuities before an inspection, I show that the firm size distribution becomes discontinuous at the threshold afterward, providing evidence of bunching behavior triggered by enforcement.

Results are robust to different controls and matching strategies. First, adding controls, matching over longer horizons, or matching on alternative firm characteristics does not change the results. Second, matching in different time periods also does not change the results. Because inspectors use a three-year lagged dataset to select firms, they select firms today based on labor information from three years ago. When I implement the event-study analysis matching firms only on three-year-lagged outcomes, I still find that the quota increases employment of disabled workers at the cost of an overall reduction in firm size. Third, matching firms only on age also delivers the same conclusions. Therefore, several methods indicate that the quota led to a decrease in firm size and an increase in the hiring of disabled workers.

The firm-level regressions are informative about the cost of the quota for disabled workers to firms but are silent on how it affects labor force participation, wages, or disability insurance take-up rates, all of which are important considerations for policymakers. To understand how the quota affects the labor market, I exploit heterogeneity in exposure to the quota for disabled workers across regions. Regions in which employment is concentrated in a few large firms are more exposed to the quota than regions with several small firms because the quota requires only large firms to hire disabled workers.

Using a difference-in-differences approach comparing high- and low-exposure regions, I find that the quota for disabled workers increased wages and the labor force participation of disabled workers. However, consistent with the results at the firm level, this came at the cost of reduced employment for non-disabled workers. Specifically, a one standard deviation increase in the exposure of a region to the quota increased the wages of disabled workers by 20% and their labor force participation by 4.5 percentage points. However, it also reduced employment of non-disabled workers by 2 percentage points and an increase in unemployment by 0.8 percentage points. These findings confirm that the quota for disabled workers promotes the participation of disabled workers but at the expense of lower economic activity.

The market-level results are robust to adding several controls and accounting for other shocks hitting the Brazilian economy. In particular, I show that controlling for exposure to the China shock, to exchange rate fluctuations, or to trade liberalization does not change the results. Furthermore, the results are robust to controlling for shocks to large firms, to the sectoral composition, or to the occupational composition. Under all these different specifications, I consistently find that exposure to the quota for disabled workers increased employment and wages of disabled workers at the cost of lower economic activity for the non-disabled.

To rationalize these results and understand how the quota affected welfare, I develop a model of the labor market for workers with disabilities. In this model, disabled and non-disabled workers must choose between participating in the labor force or staying outside of it. Disabled workers outside the labor force receive disability insurance. Firms produce by performing a range of tasks that can be carried out by either disabled or non-disabled workers, with disabled workers being potentially less productive at certain physically intensive tasks. The government enforces a quota for disabled workers, levies a payroll tax, and provides disability insurance for unemployed disabled workers. After an inspection forces firms to satisfy the quota, firms strategically choose their size to minimize the cost of satisfying the quota.

The impact of the quota on the economy depends on two key parameters: the productivity and the labor supply elasticity of disabled workers. The productivity of disabled workers captures how costly it is for firms to hire them. If disabled workers are as productive as non-disabled workers, hiring disabled workers will not have a large effect on the marginal cost of firms and, as a consequence, it will not lead to a decrease in firm size. Meanwhile, the labor supply elasticity measures the extent to which disabled workers' wages must rise to induce them into joining the workforce. When disabled workers have an inelastic labor supply, meeting the quota requires significant wage increases, driving up the cost for firms. Therefore, to understand the effect of the quota, I need to have precise estimates of the productivity of disabled workers and their labor supply elasticity, which have not been estimated in the literature.

Using estimates of the effect of the quota on firms and on the labor market, I identify the productivity of disabled workers and their labor supply elasticity. To calibrate disabled workers' productivity, I simulate quota inspections in the model and calibrate the productivity of disabled workers to match the effect of inspections on firm size in different sectors.

To calibrate the labor supply elasticity of disabled workers, I use the exposure of regions to the quota as an instrument for their wages.

According to the model, despite increasing the labor force participation of disabled workers, the quota decreased total employment, welfare, and government revenue. Specifically, the quota increased the labor force participation of disabled workers by 2.9% and their wages by 6.15%. The quota also increased the welfare of disabled workers by 1.4% in consumption-equivalent terms. However, the benefit for disabled workers came at the expense of non-disabled workers, who experienced a decrease in wages of 0.3%. Additionally, the reduction in disability insurance expenditures did not offset the decline in payroll tax revenue, forcing the government to raise payroll taxes by 1.3%. As a result, the quota decreased utilitarian welfare by 0.33%.[4]

Unlike a quota, subsidizing disabled workers can increase welfare and even raise the after-tax wages of non-disabled workers. By offering subsidies, the government encourages higher labor force participation among disabled individuals while cutting the overall cost of disability insurance. Unlike a quota—which forces all sectors to hire disabled workers—the subsidy lets disabled individuals sort into sectors where they are more productive, limiting the impact on non-disabled hiring. Consequently, the government can reduce its disability insurance expenses and lower payroll taxes on non-disabled workers. I find that the optimal subsidy for disabled workers is 19.6%. This policy would raise overall welfare by 0.03% and increase disabled labor force participation by 8.6%. These results suggest that subsidizing disabled workers is a promising alternative to reduce the cost of disability insurance and promote labor market inclusion.

This paper contributes to the literature on size-dependent policies by showing that these policies can have significant economic effects even when they do not lead firms to bunch at regulatory thresholds. Prior research has shown that size-dependent regulations distort firm behavior, lower aggregate output, and place a disproportionate burden on high-productivity firms (Guner et al. 2008, Garicano et al. 2016, Aghion et al. 2023, Gourio and Roys 2014). In developing economies, such as India and Peru, size-dependent policies have been found

[4] The policy would improve weighted welfare only if the government valued disabled workers 5.9 times more than non-disabled workers.

to create substantial distortions, even when firms have the flexibility to adjust by hiring informal workers (Amirapu and Gechter 2020, García-Santana and Pijoan-Mas 2014, Dabla-Norris et al. 2018).

The extent of bunching is closely tied to the strength of policy enforcement. Firms in Peru and Spain, for example, only cluster at size thresholds where labor market and tax regulations are strictly enforced (Viollaz 2018, Almunia and Lopez-Rodriguez 2018). Similarly, higher tax enforcement on larger firms has been shown to exacerbate misallocation by discouraging firm growth (Bachas et al. 2019).

The closest paper to mine in this literature is Caicedo et al. (2022), which studies a size-dependent apprenticeship quota in Colombia. Using the bunching of firms around the regulatory kinks of the quota, they estimate the training costs imposed on firms. Similar to my findings, their results suggest that the policy could be made more efficient by accounting for sectoral heterogeneity in compliance costs.

I contribute to this literature by examining how a quota for disabled workers in large firms—another form of size-dependent policy—can generate substantial distortions despite the absence of strong bunching at the official discontinuities. Unlike traditional size-dependent regulations, where firms adjust preemptively to remain below the threshold, I show that limited initial enforcement and firms' lack of awareness prevent such early adjustments. Instead, upon inspection, firms respond sharply by reducing their size to minimize their quota obligation. This reactive adjustment leads to a sizable contraction in overall employment. If the policy for disabled workers were enforced across the board, firms would bunch at the discontinuities of the quota and per capita GDP would fall 1.2%.

This paper contributes to the literature on disability quotas by providing a new identification strategy to estimate their effects at the firm level, examining their broader impacts on the labor market, and developing a calibrated quantitative model to assess their welfare implications. Existing research has established that disability quotas increase the hiring of disabled workers, but their effectiveness varies across contexts. Some studies find that quotas lead to bunching behavior, as firms manipulate their size to avoid compliance (Kreko and Telegdy 2022), while others show that firms prefer paying fines rather than hiring disabled workers (Barnay et al. 2019). In Austria, the quota increased the employment of disabled workers by 12%, but firms responded by adjusting their hiring of non-disabled workers to lower their quota obligations (Lalive et al. 2013). The literature has also explored the economic impact of these policies, with mixed results: in Japan, the quota had ambiguous effects on firm revenue (Mori and Sakamoto 2018), while in Saudi Arabia, a similar policy for hiring nationals reduced overall private-sector employment (Peck 2017). Duryea et al. (2024) and Berlinski and Gagete-Miranda (2024), studying the quota for disabled workers in Chile and Brazil, respectively, show that nudges and stricter enforcement can increase compliance.

I make three contributions to this literature. First, by leveraging inspections conducted by the DEO, a department specialized in enforcing the quota for disabled workers, I isolate the effect of the quota from the effects of other labor market regulations. Second, unlike previous studies that focus primarily on firm-level responses, I extend the analysis to the labor market, showing that while the quota increased employment and wages for disabled workers, these gains came at the expense of non-disabled workers. Third, I develop the first quantitative model calibrated to match both firm- and market-level effects of the quota. This model enables me to assess the welfare implications of the quota and evaluate alternative policies.

This paper is organized as follows. Section 2 describes the institutional details of the quota for disabled workers in Brazil. In Section 3, I discuss the data. In Section 4, I study the effects of the quota for disabled workers on firms. In Section 5, I study the effect of the quota on the labor market. In Section 6, I describe a model to estimate the aggregate effects of the quota for disabled workers. In Section 7, I discuss the calibration of the model. Section 8 discuss the quantitative results. Section 9 is the conclusion.

2 Institutional Setting

In this section, I describe the design of the quota for disabled workers in Brazil and its enforcement through inspections. In the empirical analysis, I leverage the design of the quota policy to identify its heterogeneous exposure across regions and exploit the exogeneity in the timing of inspections to estimate their effect on firms.

2.1 The Disability Quota

I study the quota for disabled workers established by the Brazilian federal government in 1999. According to this quota, companies with over 100 employees must have between 2% and 5% of their workforce comprised of disabled individuals. The primary objectives of the program was to reduce the cost of disability insurance and facilitate the integration of disabled individuals into the labor market. Table 1 displays the required percentage of disabled workers, which increases with the size of the company's workforce.

Table 1: **Quota for Disabled Workers as a Percentage of the Workforce**

Number of Workers	Quota for Disabled Workers
<100	0%
[100,200]	2%
[201,500]	3%
[5001,1000]	4%
>1001	5%

Notes: This table shows the percentage of disabled workers that firms are required to employ based on firm size. The first column contains firm size, measured by the number of employees. The second column shows the required percentage of disabled workers in the firm's workforce.

Who is classified as disabled. The quota applies to individuals with physical, auditory, visual, or cognitive disabilities. The law explicitly and precisely defines the impairments that qualify an individual as disabled. This definition aims to ensure that companies are hiring workers with lower work capacity who are more likely to require disability insurance. For example, the law specifies that "deformities that do not hinder job performance" should not be included in the disability quota. Appendix A.1 provides a detailed definition of physical, auditory, visual, and cognitive disabilities according to the quota for disabled workers.

To count a worker toward the quota, firms must provide two documents: a medical report characterizing the employee's disability, and a consent form signed by the worker. The medical report must be issued by a qualified professional and detail the nature of the disability, confirming it meets the legal criteria. Each disability classification requires a standardized medical examination including specific diagnostic tests and minimum clinical markers that must be met for a worker to qualify as disabled. For instance, in the case of intellectual disabilities, the report must indicate significantly below-average intellectual functioning, manifested before the age of 18, with limitations in at least two adaptive skills such as communication or personal care. Similarly, for auditory disabilities, the report must specify a minimum bilateral hearing loss threshold as defined by regulation. Medical professionals issuing these reports are legally liable for their accuracy, and providing false or misleading information can result in legal penalties and professional sanctions.[5]

Firms cannot count an employee toward the quota without their explicit consent. Given that disability status is considered sensitive personal data, firms must obtain and present a signed consent form from the worker, authorizing their inclusion in the quota and permitting the necessary documentation to be submitted for compliance verification. A firm may hire a worker without being aware of their disability status at the time of hiring. However, if the firm later discovers that the worker qualifies as disabled—through an internal survey or other means—it can count the worker toward the quota as long as the employee provides their consent. This process helps explain why some workers may change their reported disability status over time.

How firms recruit disabled workers. To meet the quota, firms in Brazil primarily rely on two recruitment strategies: targeted job ads and partnerships with specialized organizations. Companies are legally allowed to post inclusive job ads specifying that applicants must have a disability.[6] The second channel is through recruitment agencies that specialize in disabled workers. These agencies, often linked to non-profits, also reach out to disabled workers who are not actively job-hunting.

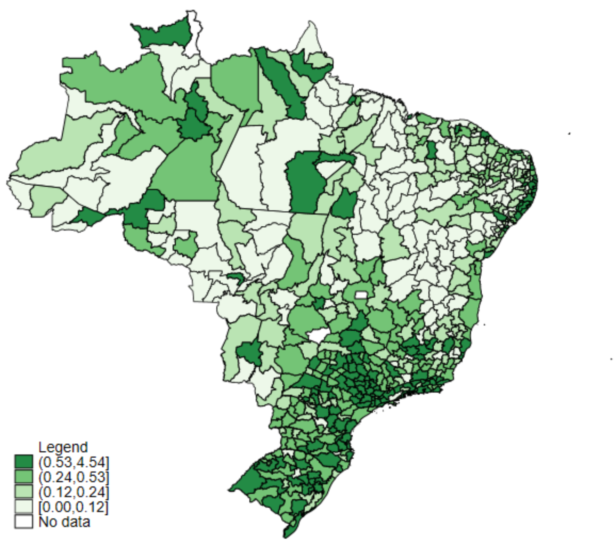
The quota for disabled workers is onerous and, in some cases, impractical. Figure 1 plots the percentage of disabled workers required to be hired by the quota in 1991, i.e., the ratio of the demand for disabled workers generated by the quota to the number of disabled workers in each microregion. In 1991, ignoring any behavioral response from agents,

[5] The document Ministério do Trabalho (2018) is used by medical doctors, firms, and inspectors to determine which workers qualify under the quota; it provides detailed descriptions of each eligible disability and outlines the necessary medical tests and criteria for classification.

[6] Several platforms specialize in job postings for workers with disabilities, such as `https://www.pcd.com.br/`.

the quota for disabled workers required firms to hire 42.6% of disabled workers. For comparison, the labor force participation of disabled workers in 1991 was 25%. Therefore, the full implementation of the quota would require an increase of 70% in the labor force participation of workers with disabilities. In 11% of the microregions in Brazil, the quota required firms to hire more disabled workers than were available in the microregion. Therefore, satisfying the quota is onerous and, in many microregions, impractical.

Figure 1: **Labor Force Participation of Disabled Workers Required by the Quota**



Notes: This figure shows the labor force participation rate of disabled workers that would be required by the quota in 1991. The labor force participation rate required by the quota is given by $\frac{\text{Demand Generated by the Quota}_r}{\text{Number of Disabled Workers}_r}$, where Demand Generated by the Quota$_r$ is the number of disabled workers required by the quota according to the firm size distribution in region r and Number of Disabled Workers$_r$ is the number of disabled workers in region r. The number of disabled workers in each region is calculated using data from the Census. The demand for disabled workers generated by the quota is calculated using data from RAIS. Both datasets are described in Section 3.

Prior to an inspection, firms do not bunch at discontinuities and do not satisfy the quota. Figure 2a presents the distribution of firms based on their distance to the nearest quota discontinuity, where the x-axis represents the number of workers relative to the closest threshold, and the y-axis shows the number of firms.[7] Unlike other size-dependent policies, where firms strategically cluster below regulatory thresholds to avoid compliance costs (Guner et al. 2008, Garicano et al. 2016, Aghion et al. 2023, Gourio and Roys 2014),

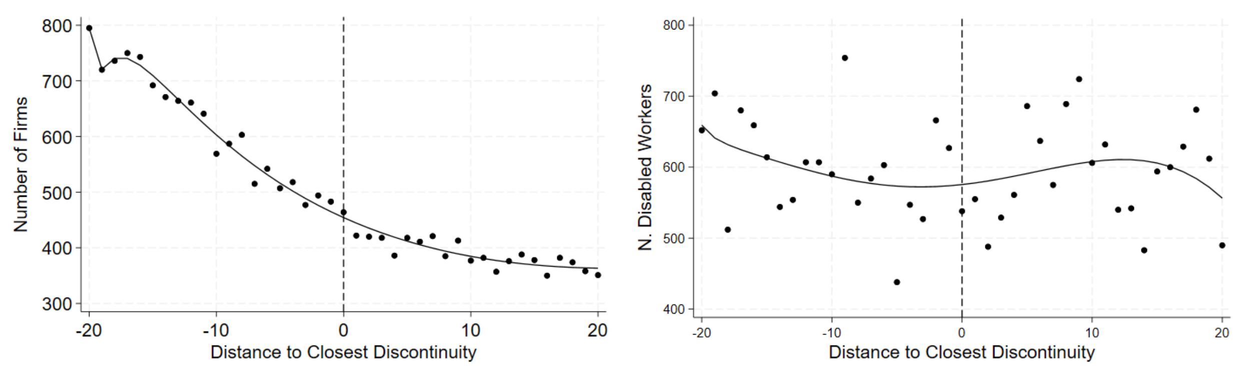
[7] Appendix Figures A.1 to A.4 reproduce Figure 2a for each discontinuity. They show that, in none of the discontinuities, there is bunching or a change in the number of disabled workers.

there is no evidence of bunching at the discontinuities of the quota for disabled workers. This suggests that, before an inspection, firms do not adjust their size preemptively to minimize their quota obligations.

Figure 2b provides an explanation for why firms are not bunching. This figure shows the number of disabled workers employed by firms based on their distance to the nearest quota discontinuity. If firms were complying with the quota, we would expect a sharp increase in the number of disabled workers at the thresholds, reflecting firms' adjustments to meet the legal requirements. However, the absence of such a pattern indicates that firms are not adhering to the quota for disabled workers. [8]

Figure 2: **Distribution of Firms and Disabled Workers Around Discontinuities**

(a) **Distribution of Firms** (b) **Number of Disabled Workers**



Notes: These figures plot the number of firms and the number of disabled workers around the discontinuities of the quota in 2016. The vertical line at 0 marks the discontinuity of the quota for disabled workers. In Figure (a), the x-axis reports the distance to the nearest discontinuity, calculated as *Number of Workers − Number of Workers at Closest Discontinuity*, and the y-axis shows the number of firms at each distance. In Figure (b), the x-axis is the same, while the y-axis displays the total number of disabled workers employed by firms at each corresponding distance from the discontinuity.

2.2 Inspections of the Disability Quota

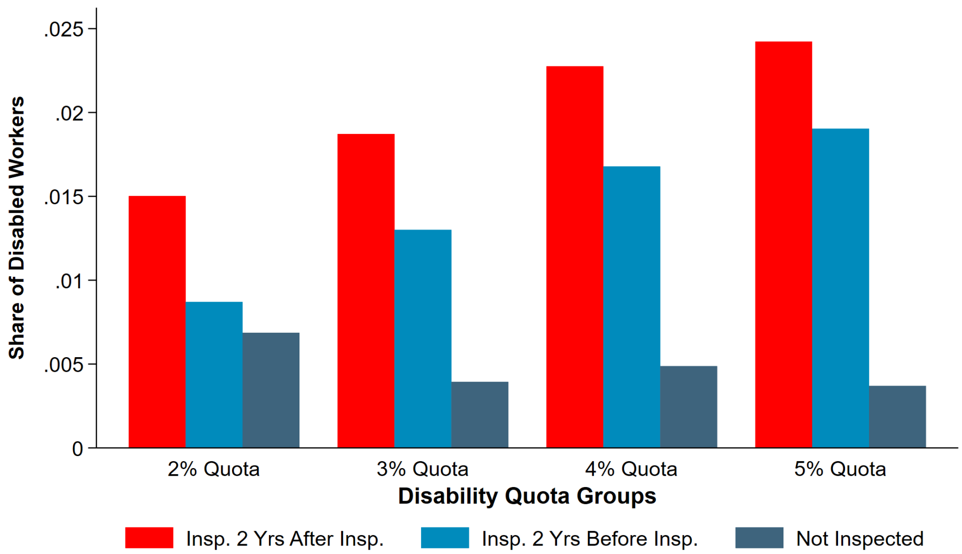
Due to the onerous requirements of the quota, many firms choose not to comply, as highlighted by 2b. To encourage compliance, the government conducts inspections specifically targeting the quota for disabled workers as a means to nudge firms into hiring workers with

[8] This lack of compliance is not unique to Brazil. Duryea et al. (2024) find that most firms in Chile do not satisfy a similar, though smaller, quota for disabled workers. Similarly, Barnay et al. (2019) find that in France, many firms prefer to pay fines rather than hire workers with disabilities.

disabilities. In this section, I provide a detailed discussion of how these inspections function as a nudge mechanism to increase the employment of disabled workers.

Most firms only hire disabled workers after an inspection. Figure 3 presents the share of disabled workers relative to the percentage required by the quota, distinguishing between three groups: firms that have never been inspected, firms after an inspection, and firms before an inspection. On average, none of these groups fully satisfy the quota. However, firms that undergo an inspection significantly increase their hiring of disabled workers.[9]

Figure 3: **Disability Share**



Notes: This figure plots the share of disabled workers in different firms. The red bar averages the share of disabled workers in firms after they are inspected. The blue bar shows the share of disabled workers in inspected firms before the inspection. The navy bar shows the share of disabled workers in firms never inspected.

Inspections of the quota are made by a specialized division. Any labor regulation inspector in Brazil can enforce the quota for disabled workers. However, the Labor Ministry has a specialized division, the National Coordination for Combating Discrimination and

[9] Inspected firms tend to employ more disabled workers than non-inspected firms even before an inspection. This is partly because inspections are more common in sectors where hiring disabled workers is more feasible, as I discuss below.

Promoting Equality of Opportunities in the Workplace, which I call the "Division of Equal Opportunity" (DEO), responsible for enforcing only the quota for disabled workers.[10]

Inspections made by DEO follow a structured procedure. Inspections of the quota follow a four-step process. First, firms are selected using lagged administrative data, based on their size and self-reported number of disabled workers. Second, firms found to be non-compliant receive a warning and are given three months to meet the quota. Third, firms that fail to comply within this period face fines or, in some cases, receive an extension. Finally, firms are short-listed and are more likely to receive follow-up inspections in the future. In that case, they are fined right away if found not to satisfy the quota for disabled workers. Since this process is key to the identification strategy, I provide a detailed discussion of each inspection step below.

Firms are selected based on past outcomes. First, the inspector selects a firm with over 100 employees. The selection is not random and is based on administrative estimates of the number of missing disabled workers, the firm's sector, and its size.[11] As the objective of the DEO is to increase the hiring of disabled workers, it targets firms with greater potential for hiring disabled workers. Firms with larger deficits of disabled workers, in less physically intense sectors, and facing larger quotas are more likely to be selected for inspection. Due to lags in the release of administrative data, inspectors select firms based on their past labor information. Given the data-intensive nature of this process, firms are generally pre-selected to be inspected at a later date.

Inspected firms have 3 months to comply with the quota. After the firm is selected, the inspector contacts the firm and requests evidence that the firm is meeting the required quota of disabled workers. The firm is required to provide a list of disabled workers, a description of their disabilities, a medical report characterizing the employee's disability, and a consent form signed by the worker agreeing to release their medical information. If

[10] Its Portuguese name is "*Coordenação Nacional de Combate à Discriminação e Promoção da Igualdade de Oportunidades no Trabalho*".

[11] To calculate these statistics, inspectors use the matched employer-employee dataset RAIS (*Relação Anual de Informações Sociais*), the same dataset used in this paper.

the firm is not meeting the quota, it has 90 days to comply.

Time extension is granted to firms actively seeking disabled workers. If the firm still fails to meet the quota after 90 days, the inspector may choose to either fine the firm or provide it with a time extension. Time extensions are only granted to firms that can prove that they are actively seeking disabled workers, such as for firms showing job ads targeting disabled workers. Once the inspection is completed, firms that have not met the quota are more likely to be visited by the inspector again in the future.

Firms not complying with the quota receive a large fine. If a firm is found not to be meeting the quota in subsequent inspections, the inspector can impose a fine immediately. The fine amount ranges from $706 to $70,645 per missing disabled worker. The fine depends on the number of times that the firm has failed inspections and whether it has been actively seeking to fill the quota. For comparison, the monthly salary of a disabled worker is $320, on average.

Fines take more than 3 years to be paid. After a fine is issued by labor inspectors, firms may first appeal administratively within the Ministry of Labor. If the fine is upheld, judicial proceedings begin in the Labor Court, where the firm presents its justification for not hiring workers with disabilities and a judge decides whether to uphold the fine. As documented by Ribeiro and Carneiro (2009), these cases often take several years to reach a conclusion, and it is common for firms to avoid paying any fines for five years or more. Indeed, in the cases studied by Ribeiro and Carneiro (2009), no firm paid a fine within the first three years following an inspection.

When a labor fine is disputed in court, the firm and the judge may reach an agreement known as an Agreement for Adjustment of Conduct.[12] Under this agreement, the firm commits to fulfilling the quota for disabled workers within a specified period set by the court. During this time frame, the firm is shielded from receiving additional fines for noncompliance, and the original fine may be waived if the quota is met as agreed. The TAC also stipulates penalties and civil sanctions in case of noncompliance. If the firm fails to meet the quota

[12] In Portuguese, this is referred to as a *Termo de Ajustamento de Conduta*(TAC).

by the end of the agreed period, it becomes liable for daily fines, and enforcement measures may include the freezing of bank accounts and the seizure of assets to ensure payment.

3 Data

In this section, I describe the datasets used in the empirical analysis. For the firm-level analysis, I use a matched employer-employee dataset merged with DEO inspection records. This dataset covers labor market outcomes for all inspected firms between 2005 and 2016. For the broader labor market analysis, I rely on census data, which provides information for the years 1980, 1991, 2000, and 2010. The census only records disability status starting in 1991.

Matched Employer-Employee. Labor outcomes come from the administrative matched employer-employee dataset RAIS. This dataset covers all formal firms in Brazil from 2005 to 2015. It includes information on worker characteristics such as wage, contractual hours, disability status, type of disability, years of education, and other demographic characteristics.

The reporting of disability status in RAIS is done by firms with the worker's consent. Since firms self-report this status, they may have an incentive to misclassify workers to manipulate compliance with the quota. However, as discussed in the institutional setting, inspectors verify this information by requiring medical proof of the disability and formal worker consent.[13]

Census. The federal government conducts a nationwide survey every 10 years. I use data from the 1980, 1991, 2000, and 2010 censuses, which provide information on labor force participation, income, disability insurance recipients, and government transfers. The 1991, 2000, and 2010 censuses also record disabilities, but only three types—auditory, visual, and cognitive—are consistently documented. To proxy for physical disability status, I use a

[13] To assess whether firm misclassification drives the results, in the empirical analysis I test whether findings are robust to using workers' reported disability status from their previous employment rather than their current employment. The fact that results are still the same under this alternative definition of disability suggests that strategic misclassification is not the primary driver of the observed effects.

dummy variable for respondents who report difficulty walking. In the robustness section, I restrict the sample to the three disability types consistently observed across censuses.

Inspections by the DEO. I obtain information on the universe of inspections of the quota for disabled workers realized by the DEO. The data covers the period from 2002 to 2015. For each inspection, I observe the name and tax ID of the firm, the number of disabled workers found, the number of disabled workers required, and the measures taken by the inspector.

General Labor Market Inspections. I also use data on all the labor market inspections realized by the Ministry of Labor and all the fines applied. For each inspection, I observe the name and tax ID of the firm, a description of the labor infraction found, and a description of the measure taken by the inspector. I use this dataset to show that inspections made by the DEO do not correlate with other labor market infractions.

4 Effect of Quota on Firms

In this section, I identify the effect of the quota for disabled workers on firms by exploiting variation from inspections of the quota. The DEO regularly inspects firms to nudge them to respect the quota for disabled workers. Inspected firms must hire disabled workers within a short period to avoid fines, resulting in random variation in the implementation of the disability quota at the firm level.

I show that after an inspection, firms reduce employment and wages despite increasing the hiring of workers with disabilities. The drop in employment is concentrated among firms near the discontinuities of the quota, in physically intensive sectors, and that employ disabled workers in occupations incompatible with their disability. These findings suggest that satisfying the quota imposes significant costs on firms, leading them to strategically reduce their size to fall below the quota thresholds and minimize the number of disabled workers they are required to hire.

4.1 Empirical Framework

To estimate the impact of the quota for disabled workers, I implement a matched differences-in-differences approach, comparing firms inspected by the DEO now to those inspected in the future. The key identifying assumption is that the timing of inspections is exogenous. To support this assumption, I present several validation exercises. First, I show that firm characteristics do not predict when inspections occur. Second, I demonstrate that inspectors rely on outdated administrative data, which reduces concerns about strategic targeting. Third, I provide evidence that quota inspections are not tied to political connections or other government policies. Fourth, I show that DEO inspections are unrelated to general labor market infractions, indicating that they focus specifically on the quota rather than broader labor regulations. Finally, I show that treatment and control firms are not statistically different on key non-matched characteristics, such as wages, education levels, and task composition.

Importance of DEO inspections for the identification. DEO inspections allow me to identify the effect of the quota because they are exclusively aimed at enforcing the quota and are assigned based on lagged administrative data rather than external complaints or firm-level shocks. In contrast, general labor market inspections, as used by Szerman (2023), are systematically correlated with firm characteristics and broader compliance issues. They are often triggered by worker complaints, judicial referrals, or workplace accidents, meaning that firms undergoing these inspections tend to be larger, growing more rapidly, or experiencing other labor-related infractions. As a result, using general labor market inspections to estimate the effect of the quota introduces endogeneity concerns, as firms subject to these inspections are likely responding to multiple factors beyond quota enforcement. A detailed discussion of these identification concerns is provided in Section B.1.1.

4.1.1 Matching Firms

I implement a difference-in-differences strategy comparing firms inspected in the current period to similar firms inspected in the future. As discussed earlier, the DEO does not randomly select firms for inspection. Instead, it targets firms with greater potential to hire disabled workers, using three main criteria: the number of employees, the number of disabled workers already employed, and the firm's sector. To account for this targeted selection, I match firms inspected today to firms with similar characteristics—size, number of disabled workers, sector, and age—that are inspected in the future.[14] This strategy ensures that the identification of the parameter of interest comes from comparing firms that were equally likely to be inspected at the time, differing only in the timing of the inspection. In the robustness section, I show that the results remain consistent under alternative matching strategies, including matching on more or fewer variables, or no matching at all.

In practice, for each firm i that underwent its first inspection in year t, I match it to a control firm j that will only be inspected in year $t+3$ or later. The firm inspected in t is the treatment firm, while its future-inspected counterpart serves as the control. I choose this short event window for two reasons. First, a shorter window allows for a larger group of potential control firms, which improves the quality of the match and increases the number of matched treatment firms. Second, a shorter horizon makes the assumption of parallel trends between control and treatment groups more reasonable. In the robustness section, I demonstrate that the results are robust to longer matching horizons.

4.1.2 Empirical Model

Main empirical model. The main empirical model consists of the following equation:

$$y_{i,p(i),t} = \beta \mathbb{I}_{i,t} \left\{ Inspection \right\} + \delta_{p(i),t} + \mu_{p(i),t} + \mu_t + \mu_i + \epsilon_{i,t} \tag{1}$$

Here, $y_{i,p(i),t}$ represents an outcome of firm i, in matched-pair $p(i)$, in year t. The dummy variable $\mathbb{I}_{i,t}\{Inspection\}$ takes the value of one after the first inspection received by firm i. For the control group, which is not inspected in the period of analysis, $\mathbb{I}_{i,t}\{Inspection\}$ is zero. The dummy variable $\mu_{p(i),t}$ takes the value 1 after the treatment firm in group $p(i)$ is inspected. It captures common trends between treatment and control in group $p(i)$. The term μ_i represents a firm fixed effect, and μ_t represents a year fixed effect. The sample is

[14] Firm age is included in the matching to control for differences in growth trajectories associated with different stages of the business life cycle.

limited to five years before the first inspection and two years after.[15]

Interpretation of parameter β: effect of the quota for disabled workers. The coefficient of interest, β, is identified from the difference in growth rates of $y_{i,p(i),t}$ between firms inspected now and those that will be inspected later. The only channel through which an inspection affects firms is by compelling them to comply with the quota under the threat of fines.[16] Hence, β can be interpreted as the causal effect of imposing the quota for disabled workers on firms.

Parallel trends test. To test parallel trends in the pre-period, I use the following specification:

$$\begin{aligned} y_{i,p(i),t} = & \sum_{j=-5}^{2} \beta_j \mathbb{I}_{i,t} \{j \textit{ Yrs. to Inspection}\} + \\ & \sum_{j=-5}^{2} \theta_j \mathbb{I}_{p(i),t} \{j \textit{ Yrs. to Inspection}\} + \mu_i + \mu_t + \epsilon_{i,t} \end{aligned} \tag{2}$$

Here, $\mathbb{I}_{i,t} \{j \textit{ Yrs. to Inspection}\}$ is a dummy variable that takes the value 1 if it has been j years since the first inspection of firm i. Similarly, $\mathbb{I}_{p(i),t} \{j \textit{ Yrs. to Inspection}\}$ is a set of dummies that lead to the first investigation among match group $p(i)$. The assumption of parallel trends in the pre-period requires that $\beta_j = 0$ if $j < 0$. The match is constructed such that $\beta_j = 0, j \in [-3, -1]$, but the first two years are not matched, allowing for the evaluation of the assumption of parallel trends.

4.1.3 Validation

The identifying assumption is that firm-level shocks do not correlate with inspection timing conditional on the matching variables. There are several pieces of evidence backing this assumption. First, firm characteristics do not predict the year of the inspection or its timing.

[15] I limit the analysis to two years after the inspection because the control firms are inspected at least three years after the treatment firms. Increasing the period of analysis would reduce the share of matched firms. In the robustness section, I show that the matching horizon does not drive the results.

[16] As discussed in Section 2, because the final decision and stimulation of the fine requires appreciation from a judge, within 2 years of an inspection, firms are only threatened with fines.

Second, inspectors select firms based on three-year lagged outcomes due to the processing time of administrative data. Third, inspections of the quota do not correlate with political connections or major policies implemented in the period. Fourth, inspections conducted by the DEO do not correlate with general labor market inspections. Fifth, treatment and control firms are similar even on non-targeted characteristics.

Firm characteristics do not predict an inspection by the DEO. Table B.1 in the Appendix shows that firm dynamics do not affect the timing of DEO inspections. In Column (1), I present coefficients from a regression of firm-level outcomes on a dummy equal to one if the firm is inspected for the first time in the following year.[17] Columns (2) to (5) replicate this exercise using a dummy indicating whether the firm is inspected two to five years in the future.

Across all specifications, Table B.1 shows that no single firm characteristic consistently predicts the timing of an upcoming inspection. Although a mild correlation exists between firm wages and inspections in the next year, this link disappears over longer horizons. Overall, these results suggest that inspectors do not target firms during a particular phase of expansion, reinforcing the assumption that the timing of inspections is exogenous.

Inspectors select firms using outdated information. The assumption that the timing of inspections is random is further supported by the institutional setting. As discussed in Section 2.2, inspectors use RAIS to select inspected firms. However, due to lags in the release of the data, firms are selected based on past outcomes. Therefore, it is unlikely that firms are being selected for inspections due to current shocks. In Section 4.3, I exploit that by matching firms on 3-year lagged outcomes and show that results remain robust.

Inspections of the quota do not correlate with political connections or other policies. In the appendix, Table B.4 reports the coefficients from regressions based on model 1, where the outcomes are variables related to firms' political connections and recipiency of major government programs. The results show no statistically significant correlation between

[17] In these regressions, the sample is limited to the period before the first inspection, preventing any correlation that might arise from the effect of inspections on subsequent firm outcomes.

DEO inspections and campaign contributions, subsidized loans, or government procurement. This suggests that DEO inspections are not politically motivated and are unlikely to be linked to other government policies, reinforcing the credibility of the identification strategy.

Inspections of the quota do not correlate with general labor market infractions. The DEO focuses exclusively on enforcing the quota for disabled workers, not on general labor regulations. Consequently, inspections for the disabled workers' quota do not correlate with other labor market infractions. In the appendix, Table B.5 shows the relationship between inspections of the quota for disabled workers and the top five most common labor infractions. Firms subject to inspections of the quota for disabled workers are not more likely to be fined for other labor market infractions. In other words, the main effect of the inspections of the quota is to nudge firms to hire more disabled workers, rather than to identify or penalize other types of labor violations. This guarantees that I can isolate the effect of enforcing the quota at the firm level.

Treatment and control firms are similar even on non-targeted characteristics. Table B.3 in the appendix presents summary statistics for treatment and control firms in the year before the inspection. The results show that these firms are not only well-matched on key variables—such as age, number of disabled workers, and total employment—but also on non-targeted characteristics, including wages, average years of education, and task content. This similarity reinforces the validity of the matching strategy and supports the assumption that control firms serve as a credible comparison group for estimating the causal effect of inspections.

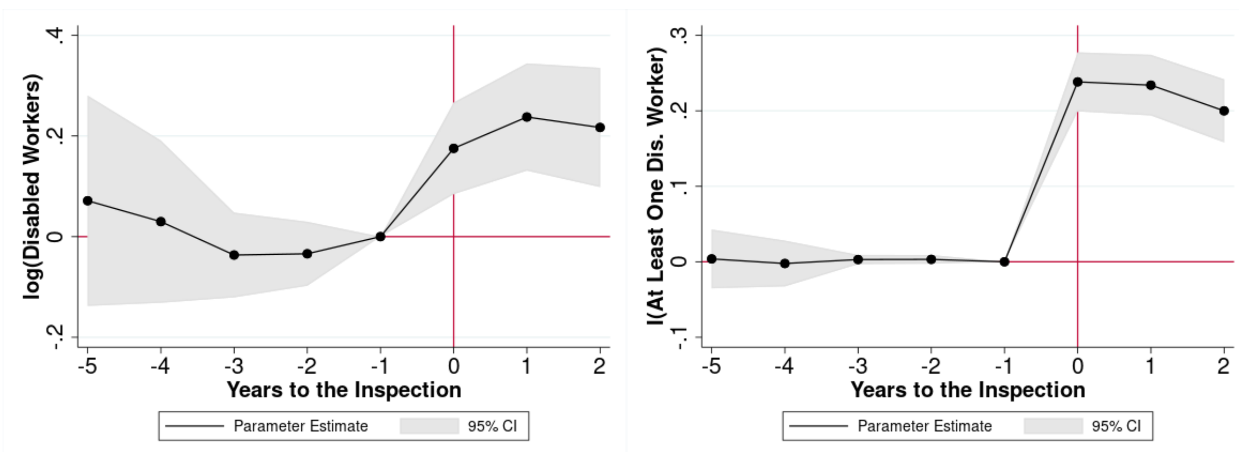
4.2 Results

In this section, I show that quota inspections increase the hiring of disabled workers but reduce employment for non-disabled workers. The decline in firm size is more pronounced among firms near a quota discontinuity and in sectors that rely heavily on physical tasks. These findings support the idea that the quota for disabled workers leads firms to shrink their workforce to lower the number of disabled employees that they are required to hire, a story consistent with other size-dependent policies.

Inspections of the quota increase the hiring of disabled workers. As a result of the inspection, firms hire more disabled workers, as illustrated in Figures 4a and 4b. Figure 4a presents the coefficients from model 2 on the log number of disabled workers. Before the inspection, control and treatment groups have similar numbers of disabled workers, even in non-matched years. After the inspection, however, the inspected firm shows a marked increase in the number of disabled employees. Two years later, the number of disabled workers at the firm is 20% higher.

Figure 4: **Inspections and Hiring of Disabled Workers**

(a) **Number of Disabled Workers** (b) **At Least One Disabled Worker**



Notes: This figure plots the dynamic estimates of the effect of inspections of the quota for disabled workers according to model 2. In Figure 4a, the variable of interest is the log number of disabled workers. In Figure 4b, the variable of interest is a dummy if the firm has at least one worker with a disability. Standard errors are clustered at the firm level.

Table 2 reports the average impact of quota inspections on various outcomes related to the hiring of disabled workers. On average, inspected firms increase their employment of disabled workers by 20% (column 1), are 22 percentage points more likely to have at least one disabled employee (column 2), and experience a 14% higher probability of satisfying the quota (column 3).

Inspections led firms to hire disabled workers at marginally lower wages and with a greater likelihood of performing physically intensive tasks. Column 4 of Table 2 shows that these new hires earn weakly lower wages than those hired before. Furthermore, Columns 5 and 6 indicate that disabled workers hired post-inspection are more frequently assigned to physically intensive and manual tasks, suggesting that they may be placed in occupations where their productivity is lower.[18]

Table 2: **Effect of Inspections on the Hiring of Disabled Workers**

	(1) *log(N. Dis. Workers)*	(2) $\mathbb{I}\{\geq$ *One Dis. Worker*$\}$	(3) $\mathbb{I}\{$*Satisfy Quota*$\}$	(4) *log(Hour Wage Disable)*	(5) *Physical Task of Dis.*	(6) *Routine Manual of Dis.*
$\mathbb{I}\{$*Inspection*$\}$	0.207***	0.224***	0.142***	-0.0400*	0.0474***	0.0444**
	(0.0562)	(0.0159)	(0.0170)	(0.0223)	(0.0183)	(0.0185)
Observations	6377	11336	11336	6377	6361	6361
R^2	0.850	0.818	0.578	0.897	0.872	0.877
Mean Dep. Var	2.406	0.547	0.219	3.86	0.077	-0.005
Mean Ind. Var	0.16	0.16	0.16	0.16	0.16	0.16

Notes: This table shows the effect of inspections of the quota for disabled workers on firms' hiring of disabled workers. *log(N. Dis. Workers)* is the log of the number of disabled workers at the firm. $\mathbb{I}\{\geq$ One Dis. Worker$\}$ is a dummy taking one if the firm has at least one disabled worker. $\mathbb{I}\{$Satisfy Quota$\}$ is a dummy taking one if the firm satisfies the quota for disabled workers. *log(Hour Wage Disable)* is the log of the hourly wage paid to disabled workers. *Physical Task of Dis.* is constructed using O*NET to measure the degree of physical task content done by workers with disabilities. Its construction is explained in detail in Section B.1.2. *Routine Manual of Dis.* measures the degree of repetitive manual tasks performed by workers with disabilities, it is constructed using ONET questions for "Arm-Hand Steadiness," "Manual Dexterity," "Finger Dexterity," "Reaction Time," "Wrist-Finger Speed," and "Speed of Limb Movement." Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3 shows that most disabled workers hired after the quota inspection come from outside the labor market. Column (1) reports the effect of inspections on the hiring of disabled workers who were working at another firm in the previous year, Column (2) shows the effect on the hiring of disabled workers not employed in the previous year, and Column (3) examines those already employed at the same firm but not previously classified as disabled. Although there is increased hiring across all three groups, the main impact of the quota is to attract disabled workers who were previously out of the labor force.

[18] Tables B.7 and B.8 in the appendix show an increase in hiring across all disability types. Table B.10 in the appendix shows the effect of inspections on different tasks performed by disabled workers.

Table 3: **Effect of Inspections on the Origin of Disabled Workers**

	(1)	(2)	(3)
	log(N. Poached Dis.)	*log(N. Unemployed Dis.)*	*log(N. Relabeled Dis.)*
$\mathbb{I}\{Inspection\}$	0.127***	0.237***	0.200***
	(0.0266)	(0.0332)	(0.0332)
Observations	9928	9928	9928
R^2	0.920	0.824	0.677
Mean Dep. Var	1.111	0.897	0.476
Mean Ind. Var	0.16	0.16	0.16

Notes: This table shows the effect of inspections of the quota for disabled workers on the employment of disabled workers from different sources. In Column (1), the outcome variable is the log of the number of disabled workers poached from another firm, plus one. In Column (2), the outcome variable is the log of the number of disabled workers hired who were not employed in the previous year, plus one. In Column (3) the outcome is the log of the number of disabled workers who, in the previous year, worked at the same firm but were not classified as disabled, plus one. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The increase in the number of workers classified as disabled who were already employed at the firm suggests some degree of reclassification. While this could reflect firms strategically relabeling workers to meet the quota, it is also plausible that firms only become aware of employees' disabilities after being informed about the quota by an inspector. Because firms can only count a worker as disabled with the worker's consent, employees who did not disclose their disability during the hiring process may later volunteer this information when surveyed following an inspection. To test how significant reclassification is, in the robustness section I show that the results are robust to defining disability status based on a worker's classification in their previous job. This suggests that, although reclassification may occur, it does not drive the observed increase in the hiring of disabled workers. [19]

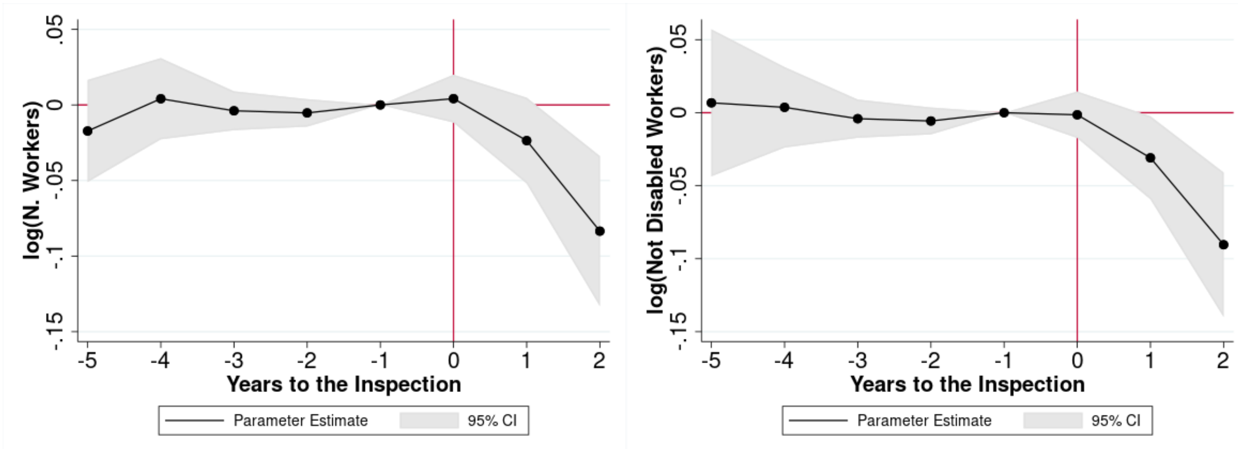
These findings confirm that inspections lead firms to hire more disabled individuals, who are predominantly drawn from outside the labor force. The newly hired workers tend to earn slightly lower wages and are disproportionately assigned to physically intensive tasks. In the subsequent paragraphs, I will argue that firms face obstacles in matching disabled workers

[19] Consistent with this conclusion, in Section 5.2, I also show that regions more exposed to the quota did not experience an increase in the share of individuals identifying as disabled.

to tasks, and these mismatches can ultimately affect firm size.

Figure 5: **Inspections and Firm Size**

(a) **Number of Workers** (b) **Number of Non-Disabled Workers**



Notes: This figure plots the dynamic estimates of the effect of inspections of the quota for disabled workers according to model 2. In Figure 5a, the variable of interest is the log number of workers. In Figure 5b, the variable of interest is the log of the number of non-disabled workers. Standard errors are clustered at the firm level.

Inspections reduce the employment of non-disabled workers. Although inspections increase the number of disabled workers, they also lead firms to shrink in overall size. Figure 5 shows the dynamic effect of inspections: before the inspection, treated and control firms follow comparable trends. At the inspection date (time zero), when firms start hiring more disabled workers, treated firms become noticeably smaller. Two years later, their total employment is significantly lower than that of comparable control firms.

Columns (1), (2), and (3) of Table 4 report the average effects of inspections on total employment, the wage bill, and the number of non-disabled workers, respectively. On average, an inspection leads to a 3% reduction in total employment and a 5% decline in the wage bill. This contraction is driven by a 4% decrease in the number of non-disabled employees.

The impact of the quota extends beyond firm size, affecting wages and the educational composition of the workforce. Table 4 shows that inspections lead to a 2% decline in hourly wages and a 0.6% decrease in the average years of education among employees.

Table 4: **Effect of Inspections on Firm Dynamics**

	(1)	(2)	(3)	(4)	(5)
	log(N. Workers)	*log(Wage Bill)*	*log(N. Not Dis. Workers)*	*log(Hourly Wage)*	*log(Avg. Years Educ.)*
$\mathbb{I}\{Inspection\}$	-0.0307**	-0.0502***	-0.0419***	-0.0223***	-0.00608**
	(0.0140)	(0.0169)	(0.0145)	(0.00773)	(0.00262)
Observations	11336	9928	11336	9928	9928
R^2	0.974	0.986	0.968	0.983	0.978
Mean Dep. Var	5.985	13.683	5.972	4.045	2.401
Mean Ind. Var	0.16	0.16	0.16	0.16	0.16

Notes: This table presents the effect of inspections of the quota for disabled workers on firm-level outcomes using model 1. *log(N. Workers)* is the log of the number of workers. *log(Wage Bill)* is the log of the wage bill. *log(N. Not Dis. Workers)* is the log of the number of non-disabled workers. $\mathbb{I}\{Decrease\ Group\ Quota\}$ is a dummy taking one if the firm decreases the percentage of disabled workers that it is required to hire. *log(Hourly Wage)* is the average hourly wage of workers at the firm. *log(Avg. Years Educ.)* is the log of the average years of education at the firm. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Firms primarily meet the quota by reducing their size. After the inspection, the total number of disabled workers that firms are required to hire decreases by 3%, according to the results in Table 5. Firms achieve this reduction by going down at the discontinuities of the quota for disabled workers, decreasing the percentage of disabled workers that they have to hire, and by avoiding becoming large enough to have to increase the percentage of disabled workers in their workforce, as illustrated in Columns 2 and 3 of Table 5.

Table 5 also indicates that firms primarily meet the quota by reducing the share of disabled workers they are required to hire. Column 4 of Table 5 shows the effect of inspections on a dummy that takes the value of one if the firm satisfies the share of disabled workers that it was required to hire the year before the firm was inspected. Table 5 indicates that an inspection only increases the probability that a firm satisfies the past quota by 6%. However, according to Table 2, an inspection increases the probability that a firm satisfies the quota by 14%. This discrepancy implies that 58% of firms that meet the quota post-inspection do so only because they decreased the number of disabled workers that they were required to hire.

Table 5: **Effect of Inspections on Firm's Quota Requirement**

	(1) *log(Disabled Quota)*	(2) $\mathbb{I}\{Decrease\ Group\ Quota\}$	(3) $\mathbb{I}\{Increase\ Group\ Quota\}$	(4) $\mathbb{I}\{Satisfy\ Past\ Quota\}$
$\mathbb{I}\{Inspection\}$	-0.0372*	0.0209***	-0.0175*	0.0631***
	(0.0211)	(0.00801)	(0.00894)	(0.0159)
Observations	9928	9928	9928	9928
R^2	0.981	0.514	0.555	0.793
Mean Dep. Var	2.509	0.036	0.086	0.14
Mean Ind. Var	0.16	0.16	0.16	0.16

Notes: This table shows the effect of inspections of the quota for disabled workers on firms' quota requirements using model 1. In Column (1), the outcome variable is the log of number of disabled workers that the firm is required to hire. In Column (2), the outcome variable is a dummy if the firm goes down a discontinuity of the quota for disabled workers, i.e., if the firm decreases the percentage of disabled workers it is required to hire. Column (3) uses a dummy indicating whether the firm increases this percentage. Column (4) includes a dummy variable that takes the value of one if the firm satisfies the quota for disabled workers based on its size in the year before the inspection. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Firm size reduction is linked to discontinuities in the quota. If firms are strategically reducing their size to meet the quota and avoid fines, we should observe a stronger decline in employment among firms near a discontinuity threshold. For instance, as shown in Table 1, firms with more than 201 workers must compose 3% of its workforce with disabled workers, while those with 200 or fewer require only 2%. A firm with 202 employees can reduce its quota from 6 to 4 disabled workers by firing just 2 non-disabled employees. In contrast, a firm with 199 workers would need to lay off 50 workers to achieve a reduction of one disabled worker in its required quota. This asymmetric incentive suggests that firms slightly above a threshold should be more likely to shrink their workforce in response to inspections.

To empirically test this prediction and investigate why firms adjust their size, I classify firms based on whether they can lower their quota requirement. For this, I calculate each firm's distance to the nearest lower discontinuity in the year prior to the inspection. For instance, in the previous example, a firm with 202 workers is just 2 employees away from the threshold at 200, whereas a firm with 199 workers is 99 employees away from the next threshold at 100. Using this measure, I divide the sample into two groups: firms that can reduce their quota requirement—those in the bottom quartile of distance to the lower discontinuity—and firms that cannot—those in the top quartile. If firms are adjusting their size as a way to decrease their quota requirement, the negative effect of inspections on firm size should be larger among firms right above a discontinuity.

Table 6 reports the effects of inspections on firms located near and far from lower discontinuities. After an inspection, firms closer to a discontinuity decrease employment by 6% and wage bill by 9%.[20] In contrast, the estimated effect of inspections on firms farther from a discontinuity is positive but not statistically significant, which is consistent with firms hiring more disabled workers without firing non-disabled workers.

These findings support the notion that firms near a discontinuity deliberately reduce their size to comply with the quota for disabled workers. In contrast, firms farther from a discontinuity tend to expand, as they accommodate more disabled workers without the option to satisfy the quota through downsizing. In the next few paragraphs, I show that the decision to downsize or hire disabled workers also depends on the ability of firms to accommodate workers with disabilities.[21]

Firms without suitable tasks for disabled workers decrease employment by more. It is likely that the impact of the quota on firm size depends on the ability of firms to assign disabled workers to suitable tasks. Firms that struggle to find appropriate roles for disabled workers should be more likely to reduce overall employment to avoid the quota requirement.

To test the importance of a firm's task content, I construct a mismatch measure using O*NET data. This measure captures the degree of incompatibility between a worker's disability type and the demands of their occupation. The measure is given by the physical task content of the occupation if the worker has a physical disability, its auditory task content if the worker has an auditory disability, the visual task content if the worker reports a visual

[20] Standard errors are larger in this specification due to the smaller sample size, as only one-fourth of the firms are included.

[21] These results suggest that firms bunch at discontinuities of the quota. In Section B.1.7, I use the manipulation test proposed by Cattaneo et al. (2018) and Cattaneo et al. (2019) to show that the firm size distribution becomes discontinuous at the quota threshold after an inspection—indicative of bunching behavior. Furthermore, this discontinuity is only observed among treatment firms and not control firms, which suggests that the discontinuity is driven by inspections of the quota.

Table 6: **Effect of Inspections According to the Distance to the Discontinuity and Disability Mismatch**

	(1)	(2)	(3)	(4)	(5)	(6)
	log(N. Workers)	*log(Wage Bill)*	*log(Earnings)*	*log(N. Workers)*	*log(Wage Bill)*	*log(Earnings)*
	Closer to Discontinuity			*Highest Disability Mismatch*		
$\mathbb{I}\{Inspection\}$	-0.0629*	-0.0896**	-0.0268*	-0.157**	-0.142*	0.0156
	(0.0371)	(0.0390)	(0.0160)	(0.0791)	(0.0851)	(0.0180)
Observations	2309	2309	2309	1056	1056	1056
	Far from Discontinuity			*Lowest Disability Mismatch*		
$\mathbb{I}\{Inspection\}$	0.0267	0.0223	-0.00438	0.150***	0.154***	0.00362
	(0.0262)	(0.0283)	(0.0127)	(0.0373)	(0.0349)	(0.0183)
Observations	2888	2888	2888	1160	1160	1160

Notes: This table shows the effect of inspections of the quota for disabled workers on firm outcomes using model 1. In Columns (1) and (2), the top panel reports the effect of inspections on firms in the bottom quartile of distance to the closest lower quota discontinuity in the year before the inspection; the bottom panel shows results for firms in the top quartile. This selection is made among both treatment and control firms. In Columns (3) and (4), the top panel includes only firms in the top quartile of disability mismatch in the year prior to inspection, while the bottom panel includes only firms in the bottom quartile. The disability mismatch of firms is defined in Section B.1.2. *log(N. Workers)* is the log of the number of workers. *log(Wage Bill)* is the log of the wage bill. *log(Earnings)* is the log of the average monthly earnings of workers. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

disability, and the cognitive task content if the worker has a cognitive disability.[22]

Table 6, using data from the year before the inspection, breaks the sample into firms in the top and bottom quartiles of disabled worker mismatch. Firms in the top quartile are those in which disabled workers are employed in occupations not well suited to their disabilities.[23] Table 6 shows that firms that have not efficiently matched disabled workers to occupations are the ones reducing employment more in response to the quota. On the other hand, firms that usually are capable of finding occupations that better fit workers with disabilities, increase employment after the quota inspection.

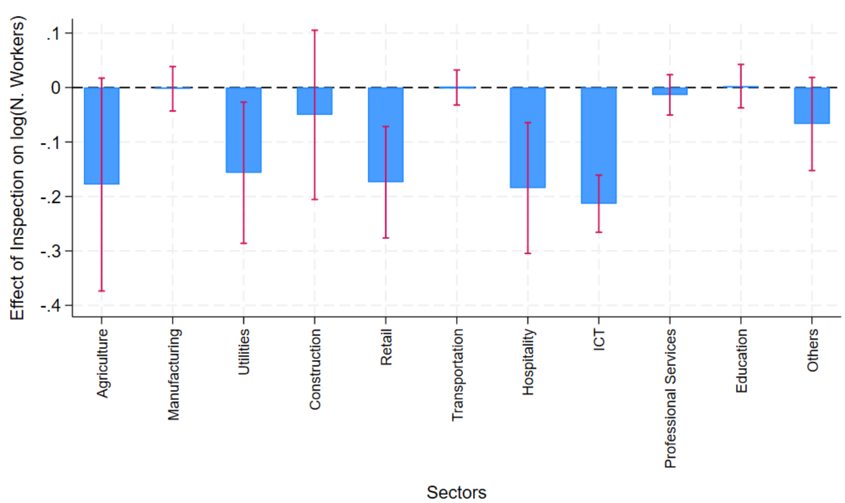
These results indicate that firms near a discontinuity, especially those with tasks unsuitable for disabled workers, reduce their size to lower their quota obligations. This behavior aligns with the idea that disabled workers are less productive in these firms, making compliance more costly.

[22] Section B.1.2 describes in detail how each task content is calculated.

[23] Because the mismatch measure requires the firm to have at least one disabled worker before the inspection, the sample is smaller.

Effect of the quota on firm size varies across sectors. Figure 6 plots the effect of quota inspections on firm size for different sectors. It shows that the effect of the quota varies greatly across sectors, indicating a high degree of heterogeneity in the productivity of disabled workers. Sectors with physically intensive tasks, such as agriculture and retail, tend to have a greater reduction in employment than those with less physically intensive tasks, such as manufacturing and education. Interestingly, inspections have a significant negative impact on employment in Information and Communication Technology (ICT), which could be attributed to the sector's high level of technical or high-skill intensity, as there may be a lack of suitable technologies that could incorporate disabled workers.

Figure 6: **Effect of Inspections on Different Sectors**



Notes: This figure plots the effect of inspections of the quota on firms in different sectors. I expand the model in 1 to allow heterogeneous effects by sectors: $y_{i,p(i),t} = \beta_{s(i)} \mathbb{I}_{i,t} \{Inspection\} + \delta_{p(i),t} + \mu_{p(i),t} + \mu_i + \epsilon_{i,t}$, where $\beta_{s(i)}$ is the effect of an inspection on firms in sector s. The remaining notation follows the one discussed in section 4.1.2. The lines show the 95% confidence interval. Standard errors are clustered at the firm level.

4.3 Robustness

Based on the results of the previous section, inspections of the quota for disabled workers led to an increase in the hiring of disabled workers but a reduction in firm size. I show that these findings are robust across a range of alternative specifications and identification strategies. In particular, the results hold when adding controls, matching over longer horizons, or varying the set of firm characteristics used in the matching procedure—including matching on more, fewer, or different characteristics. I also implement an alternative matching strategy that leverages the information available to inspectors at the time of firm selection. Furthermore, I show that, following an inspection, firms begin to bunch at the quota discontinuities—consistent with strategic downsizing to reduce compliance cost. Across all these empirical strategies, the core result remains: inspections increase the employment of disabled workers while prompting a contraction in overall firm size.

Bunching after inspection. In Section B.1.7, I provide supporting evidence that, two years after an inspection, there is a statistically significant increase in the number of firms just below the quota threshold. Using the manipulation test proposed by Cattaneo et al. (2018) and Cattaneo et al. (2019), I show that the firm size distribution becomes discontinuous at the quota threshold after an inspection—indicative of bunching behavior. This pattern is not observed among control firms, suggesting that the effect is driven by quota enforcement rather than general firm dynamics. One important caveat is that the number of firms used in this analysis is relatively small—621 inspected firms—compared to other studies such as Garicano et al. (2016), which analyzed roughly 10,000 firms.

Matching only on firm age. I implement the event-study framework matching firms only on their age. Since growth rates can differ by a firm's stage in the business life cycle, matching on age is the most parsimonious specification. Although event-study designs can sometimes be sensitive to the matching procedure, this simplified approach confirms our earlier results. Table B.11 shows that inspections of the quota for disabled workers still increase the hiring of disabled workers while reducing the employment of non-disabled workers. Moreover, firms continue to manipulate their size to lower the quota requirement, an outcome consistent with the main conclusion.

Matching on other firm characteristics. Results are robust to matching firms on other labor market outcomes. In Table B.19, I show the estimates of the effect of the quota matching treated and control firms also on their hourly wage, number of establishments, share of high-school dropouts, sector, employment, number of disabled workers, and age in the three years before the inspection. The number of successful matches decreases substantially which reduces the sample and increases standard errors. Still, I find that the quota increased the hiring of disabled workers and decreased firm size by 2.1%, not statistically different from the findings in the baseline specification.

Matching over longer and shorter horizon. Tables B.15 and B.16 show the effect of inspections under different matching windows. Treatment and control firms are matched on the two (Table B.15) to five (Table B.16) years leading to the inspection. The results are still the same: the inspection leads to large increases in the hiring of disabled workers and lower firm size.

Tables B.17 and B.18 show the estimates of the effect of an inspection of the quota for disabled workers requiring control firms to be inspected up to four to six years after the treatment firms. The estimated effect of the quota is larger but less precisely estimated, which is expected because the number of observations drop and because treated firms receive multiple visits from inspectors.

Lagged match. Inspectors select firms using lagged firm information. Specifically, inspectors use RAIS to select firms, which usually comes with a three-year lag. Inspired by this, I match firms using only the labor outcome of firms that are in the information set of inspectors. I reproduce equation 1 but match treatment and control firms on outcomes five to two years before the inspection. This robustness test is especially important because it allows me to test if parallel trends hold in the two years closest to the inspection, which once again would validate the identifying assumption that inspectors are not targeting high-growth firms.

Figure B.6 shows the dynamic estimates of the effect of inspections on the number of disabled workers and employment. Despite matching on firms' outcomes five to three years before the inspection, treatment and control groups have similar employment and numbers of disabled workers in the two years before the inspection. After the inspection, employment of disabled workers significantly increased at the treated firms while total employment decreased. Table B.20 shows that, on average, inspected firms decrease employment by 2.6%

and increase the hiring of disabled workers by 34%.

Controls. Tables B.12, B.13, and B.14 show that the results are robust to adding controls. Results are robust to adding a 2-digit sector-year fixed effect, which captures sector-level shocks, municipality-level fixed effects, capturing potential spillovers, and a match-year fixed effect.

Dealing with zeros. Several firms do not hire workers with disabilities prior to the inspection. Consequently, Table 2 separates the extensive margin (whether a firm hires disabled workers at all) from the intensive margin (the number of disabled workers employed). As a complementary check, Table B.21 confirms that, on average, firms hire approximately seven disabled workers once inspected. Importantly, this relationship holds regardless of the functional form, indicating a robust, sizable increase in the hiring of disabled workers following an inspection.

Firms are not substituting formal workers with informal labor. An important concern is that inspected firms might reduce their formal workforce while secretly hiring more workers informally. Although measuring informal hiring directly is difficult, we can track fines imposed on firms for employing informal workers as a proxy. If firms were indeed hiring workers informally, they should be more likely to be fined for it. However, as Table B.5 in the Appendix shows, inspections do not increase the likelihood of receiving other labor market fines nor fines for hiring informal workers. Therefore, based on the available evidence, it is more likely that firms are not hiring more workers informally.

The effect on firm size cannot be explained by fines. As discussed in Section 2, labor fines issued by inspectors must first be upheld by a labor judge and can be appealed through several legal instances. Firms often negotiate agreements with the judiciary to comply with the quota within a set time frame, which voids the fine. As a result, fines are rarely paid within two years of the inspection (Ribeiro and Carneiro 2009), making it unlikely that they drive the observed short-run effects on firm size. A potential concern, however, is that firms may anticipate future penalties and reduce employment preemptively to build savings.

If this were the primary mechanism behind the employment response, we would expect firms that reduce employment more after an inspection—those near quota discontinuities or with high mismatch between tasks and disabilities—to be fined more frequently or face higher penalties. Table B.22 in the Appendix shows that this is not the case: there is no statistically significant difference in the likelihood or size of fines between firms with high or low mismatch, or between those close to or far from a discontinuity. These findings, combined with the institutional constraints around fines, suggest that the decline in firm size following inspections is not driven by the financial burden of fines but rather by the cost of complying with the quota itself.

Firms are not only reclassifying workers as disabled. To address potential relabeling of workers as disabled, I provide both an upper and lower bound on the number of disabled workers hired by firms. Rather than relying solely on firm classifications, I use each worker's full labor market history in RAIS to infer their disability status. I construct two alternative classifications: one in which a worker is considered disabled only if they have always been recorded as such in RAIS (a conservative lower bound) and another where a worker is classified as disabled if they have been recorded as such at least once (a more inclusive upper bound).Table B.23 presents the effect of inspections on the hiring of disabled workers under these different classifications. The results show that inspections increased the hiring of disabled workers by 16% to 20%, depending on the definition used. This suggests that, regardless of how firms classify disabled workers, inspections led to a significant rise in their employment.[24]

5 Effect of Disabled Quota on the Labor Market

Firm-level regressions fail to consider the broader impact of the quota for disabled workers on the economy. They cannot tell how the quota affects labor force participation, wages, or disability insurance take-up rates, all of which are vital considerations for policymakers. In this section, I exploit heterogeneous exposure to the quota for disabled workers across

[24] Consistent with these results, I show in Section 5.2 that the quota did not lead to an increase in the number of individuals who identify as disabled.

labor markets to understand how it affects wages and labor force participation. In line with the firm-level results, I show that the quota for disabled workers increased the labor force participation of workers with disabilities at the cost of non-disabled workers.

5.1 Empirical Framework

5.1.1 Heterogeneous Exposure

Although the quota for disabled workers is a national policy, its impact across regions varied depending on the size of firms in each region. The quota only applies to firms with more than 100 workers, meaning that regions in which employment is concentrated among a few large firms are more exposed to the quota than regions with several small firms. Consequently, the effect of the quota for disabled workers is heterogeneous across labor markets, with heterogeneity depending on the firm size distribution.

I measure the exposure of region r to the quota for disabled workers as

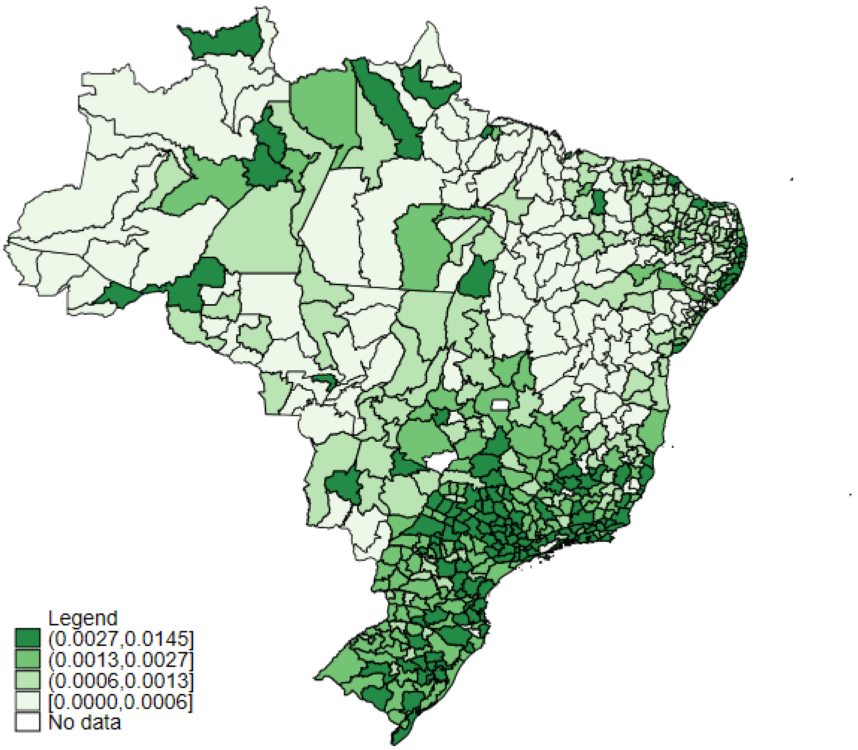
$$exposure_r = \frac{N.\ Disabled\ Workers\ Required\ by\ the\ Quota_{r,91}}{Population_{r,91}} \tag{3}$$

where $N.\ Disabled\ Workers\ Required\ by\ the\ Quota_{r,91}$ is the number of disabled workers required to be employed by the quota according to the firm size distribution in region r in 1991. Each r region is a microregion, Brazil's equivalent of a commuting zone in the US.[25] $Population_{r,91}$ is the population in region r in 1991. Figure 7 shows the distribution of $exposure_r$.[26] In the robustness section, I show that the main conclusion is robust to different exposure measures.

[25] A microregion is a group of cities economically and socially connected classified by the Brazilian Institute of Geography and Statistics.

[26] To calculate the number of disabled workers required in each region, I need to make assumptions about the allocation of disabled workers within multi-establishment firms. In the main part of the paper, I assume that multi-establishment firms distribute disabled workers in proportion to the number of workers across regions. In the robustness section, I show that this assumption does not affect the results.

Figure 7: **Disabled Demand Across Regions in 2010**



Notes: This figure plots the exposure of different microregions to the quota for disabled workers, defined in equation 3.

5.1.2 Empirical Model

The main empirical model to identify the effect of the disability quota on the labor market is given by

$$y_{r,t} = \theta \times exposure_r \times \mathbb{I}\{t \geq 2000\} + X'_{r,t}\alpha + \mu_t + \mu_r + \epsilon_{r,t} \tag{4}$$

where $y_{r,t}$ is an outcome of region r in year t. The variable $exposure_r$ captures the relative demand for disabled workers created by the quota law, $\mathbb{I}\{t \geq 2000\}$ is a dummy taking 1 after the creation of the disability quota, $X_{r,t}$ is a set of controls, μ_t is a time fixed effect and μ_r is a region fixed effect.[27] To facilitate interpretation, I normalize the exposure measure to have a mean of zero and a standard deviation of 1.

To estimate the effect of the quota on labor force participation and social security con-

[27] As controls, I use the average firm size in 1991 and the outcome variable in 1991, $y_{r,91}$, interacted with year fixed effects.

tributions, I estimate model 4 on data from censuses. The census has been conducted approximately every 10 years, and since 1991, it has collected information on disability status.

The parameter of interest is θ. It captures the effect of exposure to the quota for disabled workers on outcome $y_{i,t}$. As is common in difference-in-differences analysis, the identifying assumption is that high- and low-exposure regions exhibit parallel trends.

To test for parallel trends in the pre-period, I use the following dynamic model:

$$y_{r,t} = \kappa_t \times exposure_r + X'_{r,t}\alpha + \mu_t + \mu_r + \epsilon_{i,r,t} \tag{5}$$

where κ_t is the effect of exposure to the quota on labor market outcomes in year t, $t \in \{1980, 1991, 2000, 2010\}$. If parallel trends in the pre-period hold, $\kappa_t \approx 0, \forall t \leq 1991$. Because the census of 1980 did not ask respondents about disability status, I can only estimate the dynamic model to labor market outcomes including disabled and non-disabled workers.

5.2 Effect on the Labor Market

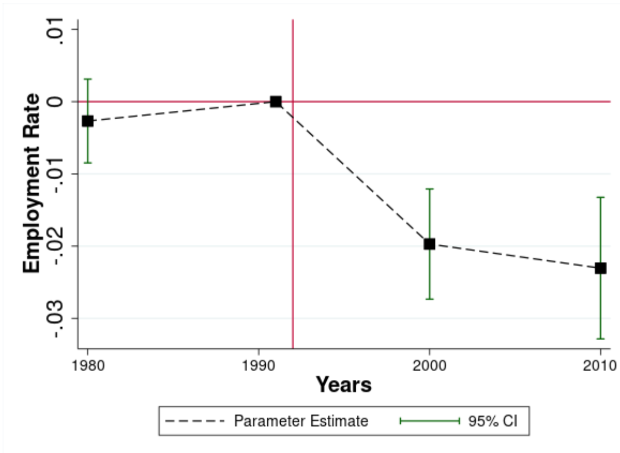
I start by studying the effect of the quota for disabled workers on the labor market, aggregating disabled and non-disabled workers. I show that the quota decreased employment and social security contributions while increasing the unemployment rate, consistent with the firm-level effects.

The estimates of the dynamic model (shown in Figure 8a) reveal that regions with higher exposure to the quota had a decline in employment rates compared to those with lower exposure. Prior to the quota's introduction in 1991, both groups exhibited similar employment trends. However, after its implementation, the difference between the two groups became apparent. As of 2010, which marks 19 years since the quota's creation, regions with one standard deviation more exposure to the quota experienced a decrease in the employment rate by 2 percentage points.

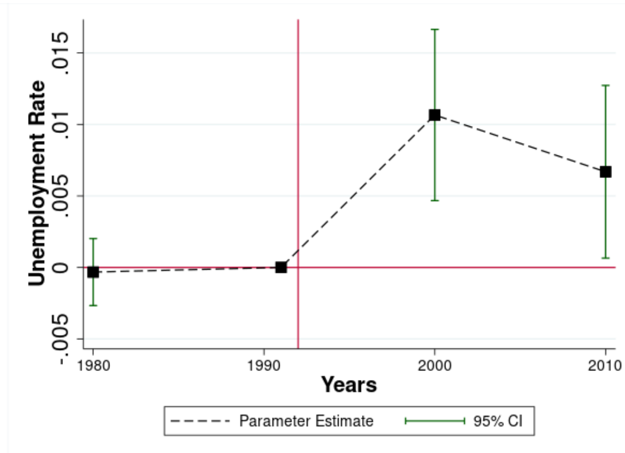
Figures 8b and 8c show that the quota for disabled workers led to an increase in unemployment and a decrease in social security contributions. Before the introduction of the quota, regions had similar trends in unemployment and social security contributions. How-

Figure 8: **Effect of Quota for Disabled Workers on the Labor Market**

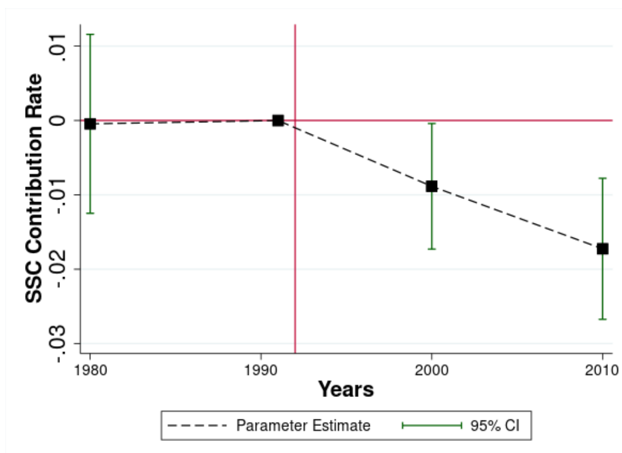
(a) **Employment**



(b) **Unemployment**



(c) **Social Security Contribution**



Notes: This figure plots the dynamic estimates of the effect of the quota for disabled workers on regional labor market outcomes according to model 5. In Figure 8a, the variable of interest is the employment rate. In Figure 8b, the variable of interest is the unemployment rate. And in Figure 8c, the variable of interest is the share of workers making social security contributions. The data come from the Brazilian Census of 1980, 1991, 2000, and 2010. The standard errors are clustered at the microregion level.

ever, after the quota was introduced, there was a sharp increase in unemployment rates. Because the share of unemployed workers increased, the number of individuals making social security contributions decreased.

Table 7 presents the main estimates, indicating that for every one standard deviation increase in the exposure to the quota for disabled workers, employment decreased by 2 percentage points and unemployment increased by 0.8 percentage points.

These results are in line with the firm-level estimates, reinforcing the conclusion that the quota for disabled workers had unintended negative effects on firms. At the firm level, the quota led firms to a reduction in employment, as firms strategically downsized to reduce their quota obligations. This contraction at the firm level translates into broader labor market effects: regions more exposed to the quota experienced lower employment rates, higher unemployment, and a decline in social security contributions.

Table 7: **Effect of Quota for Disabled Workers on the Labor Market**

	(1) *Employment Rate*	(2) *Unemployment Rate*	(3) *Labor Force*	(4) *Shr. SSC Contrib.*
Exposure	-0.0201***	0.00883***	-0.000432	-0.0128**
	(0.00384)	(0.00263)	(0.00210)	(0.00570)
Observations	2211	2211	2211	2211
R^2	0.961	0.986	0.922	0.972
# Regions	557	557	557	557
Mean Dep. Var	0.459	0.322	0.684	0.36

Notes: This table reports the effect of exposure to the quota for disabled workers on regional labor market outcomes according to model 4. The outcomes include both disabled and non-disabled workers. The variable of interest in Column 1 is the employment rate, in Column 2 the unemployment rate, in Column 3 the labor force participation, and in Column 4 the share of workers making social security contributions. The data come from the Brazilian Census of 1980, 1991, 2000, and 2010. Standard errors are clustered at the microregion level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.3 Effect on the Labor Market of Disabled Workers

The quota had a positive impact on the labor market of disabled workers, increasing their employment rate, labor force participation, and wages, according to results in Table 8.[28] Column 1 of Table 8 provides an estimate of Model 4 on the employment rate of disabled workers. According to these results, increasing exposure to the quota by one standard deviation increased the employment of disabled workers by 4.5 percentage points.

Columns 2 and 3 of Table 8 indicate that the quota also led to a decrease in the unemployment rate and an increase in labor force participation among disabled workers. As a

[28] Because the census only records disabilities after 1990, I can't check for pre-period parallel trends for disabled workers specifically. However, given that parallel trends hold for the whole market, it is also likely that they hold for disabled workers as well. In the robustness section, I show that adding controls or changing the exposure metric does not change the conclusions.

result, there was a decrease in work-age retirement among disabled workers and an increase in social security contributions.

Finally, Column 6 of Table 8 shows that the increased demand for disabled workers also had a positive impact on their wages. Specifically, a one standard deviation increase in the exposure to the quota led to a 19.8% increase in the average wage of disabled workers.

Table 8: **Effect of Quota for Disabled Workers on the Labor Market of Disabled Workers**

	(1) *Employment Rate*	(2) *Unemployment Rate*	(3) *Labor Force*	(4) *Work-Age Retirement*	(5) *Shr. SSC Contrib.*	(6) *log(Avg. Wage)*
Exposure	0.0454***	-0.0362***	0.0310***	-0.0306***	0.123***	0.198***
	(0.00644)	(0.00595)	(0.00353)	(0.00336)	(0.0129)	(0.0235)
Observations	1516	1516	1664	1664	1575	1571
R^2	0.888	0.895	0.796	0.825	0.838	0.986
# Regions	506	506	555	555	526	524
Mean Dep. Var	0.588	0.393	0.25	0.289	0.408	7.586

Notes: This table reports the effect of exposure to the quota for disabled workers on regional labor market outcomes of workers with disabilities according to model 4. The variable of interest in Column 1 is the employment rate, in Column 2 the unemployment rate, in Column 3 the labor force participation, in Column 4 the share of retired individuals aged between 18 and 50, in Column 5 the number of workers making social security contributions, and in Column 6 the wages. The data come from the Brazilian Census of 1991, 2000, and 2010. The 1980 Census does not include identifiers for disability. The standard errors are clustered at the microregion level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.4 Robustness

The quota for disabled workers increased employment and labor force participation among disabled workers, but at the expense of non-disabled workers. I show that this finding remains valid even when using alternative exposure measures and adding controls, as well as with different definitions of disability status.

5.4.1 Controls

The results are robust even when adding various controls, as shown in Table B.24 in the appendix.

Controlling for a polynomial on firm size. It could be the case that the results are affected by shocks to large firms. To assess that, Table B.24 displays the main results adding as controls the average firm size and the standard deviation of the firm size distribution in 1991 interacted with year. For the same reason, in Column 3, I control for a polynomial of average firm size and standard deviation of firm size in 1991. Because the results are not affected by controlling for the firm size distribution, I conclude that the results are not driven by shocks affecting large firms.

Controlling for occupation and sector composition. In Columns 4 and 5 of Table B.24, I control for the share of workers in different occupations and sectoral GDP, respectively. These controls have the objective of accounting for sectoral or occupational shocks that correlate with the exposure measure.[29] I still find that the quota increased the employment of disabled workers and decreased the employment of non-disabled workers.

Controlling for sector-year fixed effects. In Column 6 of Table B.24, I add state-year fixed effects as controls, which has the objective of capturing any state-level shock. I again find that the quota decreased employment of non-disabled workers and increased employment of disabled workers. However, the point estimate of the effect on non-disabled workers is smaller and less precisely estimated.

Saturated specification. Finally, in the last Column of Table B.24, all the controls discussed are added. Despite adding an unreasonable number of controls and losing a lot of variation, I still find that the quota for disabled workers significantly increased the employment of disabled workers and decreased the employment of non-disabled workers.

5.4.2 Alternative Exposure Measures

In Tables B.25 and B.26 in the appendix, I show that results are robust to three alternative measures of regional exposure to the quota.

[29] I control for the share of workers in each one-digit CBO91 classification and the GDP of the agriculture, manufacturing, and service sectors.

Limiting exposure to single-establishment firms. First, in the second panel of Tables B.25 and B.26, instead of using all firms in a region to calculate the number of disabled workers required to be hired by the quota, I use only those firms that have all their establishments in one region. By limiting the sample to these firms, I can test if assumptions about the allocation of disabled workers within multi-establishment firms influence the results. I still find that the quota increased the employment of disabled workers at the cost of non-disabled workers.

Log of the number of disabled workers required by the quota. Second, in the third panel of Figures B.25 and B.26, I use the logarithm of the number of disabled workers required to be hired in each region as an alternative exposure measure. The conclusions remain the same.

Normalization by the supply of disabled workers. Lastly, in the third alternative exposure measure, I normalize the demand for disabled workers generated by the quota by the number of disabled workers in the region, rather than the total population. I still find that a larger exposure to the quota for disabled workers leads to a decrease in the overall employment rate and social security contribution, while increasing labor force participation and employment of disabled workers.

5.4.3 Alternative Definition of Disability and Mobility

Alternative Definition of Disability. As mentioned in Section 3, the census does not provide information on whether individuals have a physical disability. Therefore, I use a dummy variable based on whether individuals have difficulty walking as a proxy for physical disability. In Table B.27, I restrict the sample to individuals with auditive, visual, or cognitive disabilities. Despite this sample restriction, the results remain unchanged.

Mobility or Self-Identification. Column 7 of Table B.27 shows that the quota has not increased the number of individuals identifying as disabled in a region. This also implies that disabled workers have not moved between regions in response to the quota.

6 Model

In this section, I present a model to study how the quota for disabled workers affects firms, workers, and the government. The model has two key features. First, it accounts for the possibility that disabled workers may have lower productivity compared to non-disabled workers for certain physically demanding tasks. Second, the model assumes that disabled workers who are not employed receive disability insurance.

In the model, inspected firms maximize profit by choosing jointly their demand for disabled and non-disabled workers constrained to satisfy the quota. If the government forces firms to hire disabled workers with a quota, it will reduce expenditure on disability insurance but increase the marginal cost of production. To avoid the quota, firms will choose to employ fewer non-disabled workers, as seen in the data. The net effect of the quota will depend on the productivity of disabled workers and on their labor supply elasticity, which I estimate using the identified effect of the quota from the empirical sections.

Demographics. The economy is inhabited by a continuum of workers and firms. Workers can be disabled or non-disabled. They consume, receive disability insurance, and supply labor. The utility function of workers is given by:

$$u_i(c, l) = log(c) - \gamma_i l \tag{6}$$

where c is consumption, $l \in \{0, 1\}$ is labor supply, and γ_i is the disutility of working for worker i.

Firms produce a homogeneous good using labor from disabled or non-disabled workers. The government taxes labor income, provides disability insurance, and imposes a quota for disabled workers. However, due to a lack of enforcement, only a fraction of firms is required to satisfy the quota. The profit π from firms is equally divided among all workers.

Non-Disabled Workers. A fraction of $1 - \lambda_d$ workers are non-disabled. Non-disabled workers receive a wage of w_n and experience disutility of $\gamma_i \sim Frechet(\mu_n)$ if they work, where μ_n is the labor supply elasticity of non-disabled workers. They join the labor force if

$$\log(w_n + \pi) - \gamma_i > \log(\pi)$$

Using that γ_i follows a Frechet distribution, I can write the labor supply of non-disabled workers as

$$\exp\left(\log(\pi) - \log(w_n + \pi)\right)^{-\mu_n}$$

Disabled Workers. A fraction of λ_d workers are disabled. Disabled workers receive a wage of w_d and experience disutility of $\gamma_i \sim Frechet(\mu_d)$ if they choose to work.[30] If a disabled worker chooses not to participate in the labor force, they receive disability insurance T. Therefore, disabled and non-disabled workers differ in their wages, labor supply elasticity, and disability insurance. A disabled worker i will join the labor force if

$$\log(w_d + \pi) - \gamma_i \geq \log(T + \pi)$$

From the utility maximization of disabled workers, their labor force participation is given by:

$$\exp(-(\log(w_d + \pi) - \log(T + \pi))^{-\mu_d}) \tag{7}$$

Government. The government imposes a marginal tax rate τ on labor income, provides disability insurance T, and has exogenous expenditure G. I assume that the government observes disability status.[31] In addition, the government requires firms to meet a quota for disabled workers. Specifically, a firm that hires n_j non-disabled workers must also employ at least $\bar{d}(n_j)$ disabled workers. However, due to weak enforcement, only a fraction θ of firms are required to satisfy the quota.

[30] Unlike in the United States, where the Americans with Disability Act forbids firms from discriminating in favor of disabled workers, many countries do not have such regulations. In Brazil, firms are allowed to post job ads exclusively for disabled workers.

[31] In Section A.1, I discuss the strict definitions of disabilities imposed by the quota for disabled workers, which limits firms' ability to manipulate workers' disability status. As discussed in Sections 4 and 5.2, the results are not driven by firms or workers changing their disability status.

Tasks. Firms have to fulfill a measure one of tasks $x \in [0,1]$ to produce. Let task $y(x)$ be the output of task x. The production function of firm j is then

$$Y_j = z_j \left[\left(\int y_j(x)^{\frac{\lambda-1}{\lambda}} dx \right)^{\frac{\lambda}{\lambda-1}} \right]^{\alpha}$$

where z_j is the TFP productivity of firm j, $y_j(x)$ is the output of task x by firm j, λ is the elasticity of substitution across tasks, and α is the degree of decreasing returns to scale.

The production of task x can be performed by either a disabled or a non-disabled worker. The productivity of a disabled worker for task x is x^{κ_j}, while the productivity of a non-disabled worker is 1. Therefore, κ_j measures the relative productivity of disabled workers. The rationale behind this is the fact that tasks such as carrying heavy materials or climbing stairs may be more challenging for disabled workers, though there are tasks they can perform as effectively as non-disabled workers.[32]

The output of task x is

$$y_j(x) = n_j(x) + x^{\kappa_j} d_j(x)$$

where $n_j(x)$ and $d_j(x)$ are, respectively, the number of non-disabled and disabled workers allocated to task x by firm j.

Firm Heterogeneity. Let $\xi_j \in \{0,1\}$ be a dummy taking the value of one if firm j is constantly monitored and, therefore, has to satisfy the quota for disabled workers. I assume that firm heterogeneity is determined by a three-dimensional distribution:

$$(z_j, \kappa_j, \xi_j) \sim \Gamma$$

where z_j is the TFP productivity, κ_j is productivity of disabled workers, and ξ_j identifies if the firm has to satisfy the quota.

[32] Another possibility to model the productivity of disabled workers is to assume that there is a set of tasks that can be performed only by non-disabled workers, in the spirit of Acemoglu and Restrepo (2020). To keep the problem tractable and avoid corner solutions, I use the main functional form discussed in the paper.

Firm's Problem. Due to the quota for disabled workers imposed by the government, $\bar{d}$, some firms are required to hire a minimum amount of disabled workers. Firms have to satisfy

$$\int d_j(x)dx \geq \xi_j \bar{d}\left(\int n_j(x)dx\right)$$

where $\int d_j(x)dx$ is the number of disabled workers hired at firm j and $\bar{d}\left(\int n_j(x)dx\right)$ is the number of disabled workers required by the quota from a firm with $\int n_j(x)dx$ disabled workers. If the firm is not enforced through inspections, $\xi_j = 0$ and the firm doesn't have a quota.

The problem of firm j is:

$$\max_{Y,y(x),n(x),d(x)} Y - \int (1+\tau)w_n n(x)dx - \int (1+\tau)w_d d(x)dx - \xi_j \mathbb{I}\left\{\int d(x)dx > 0\right\} \tag{8}$$

s.t.

$$Y = z_j\left[\left(\int y(x)^{\frac{\lambda-1}{\lambda}}dx\right)^{\frac{\lambda}{\lambda-1}}\right]^{\alpha}$$

$$y(x) = n(x) + x^{\kappa}d(x)$$

$$\int d(x)dx \geq x_j \bar{d}\left(\int n(x)dx\right)$$

6.1 Equilibrium

The labor market clearing condition requires the supply and the demand of workers to be equal:

$$(1-\lambda_d)\exp\left(\log(\pi) - \log(w_n+\pi)\right)^{-\mu_n} = \int_j \int_x n_j(x)dxd\Gamma \tag{9}$$

$$\lambda_d \exp(-(\log(w_d+\pi) - \log(T+\pi))^{-\mu}) = \int_j \int_x d_j(x)dxd\Gamma \tag{10}$$

The budget constraint of the government is given by

$$\tau\left(w_n \int_j \int_x n_j(x)dxd\Gamma + w_d \int_j \int_x d_j(x)dxd\Gamma\right) = T\left(\lambda_d - \int_j \int_x d_j(x)dxd\Gamma\right) + G \tag{11}$$

where the left hand side is the revenue from payroll taxes and the right hand side is the total expenditure on disability insurance plus the exogenous expenditure G.

Given fiscal policy $\{\tau, T, d(.)\}$, an equilibrium is defined by a solution to the firm's problem 8, $\{Y_j, \{y_j(x), n_j(x), d_j(x)\}_{x\in[0,1]}\}$, prices, $\{w_n, w_d\}$, and a solution to the worker's problem such that the labor market clears and the government budget constraint is satisfied.

7 Calibration and Identification of Model Parameters

In this section, I use estimates of the quota's impact at both the firm and market levels to calibrate the model. The calibration proceeds in four steps. First, I calibrate parameters related to the government and production function using standard values from the literature. Second, I estimate the labor supply elasticity of disabled workers by using the quota's effect on their wages and employment, as explained in section 5. Third, I calibrate the productivity of disabled workers by matching the effect of quota inspections on firm size, as discussed in section 4. Finally, I identify the distribution of firms' TFP by targeting firms with fewer than 95 workers, which are not directly affected by the quota.[33]

Labor Supply Elasticity. I calibrate the labor supply elasticity to reproduce the impact of the quota for disabled workers on wages and on the labor force participation of disabled workers. Using equation 7, we can express the labor force participation of disabled workers as:

$$\log(\text{labor force disabled}) = \mu_d \log(w_d + \pi) - \mu_d \log(T + \pi) \approx \mu_d \log(w_d) + H(\pi, T) \quad (12)$$

where H is a function of π and T. Assuming that the quota for disabled workers only affects aggregate profit, and not regional profits, $H(\pi, T)$ is absorbed by the time fixed effect. Therefore, I can use the exposure measure in 3 as an instrument for wages to identify the

[33] For simplicity, I model the enforcement of the quota as an exogenous shock to its adoption, reflecting the nature of DEO inspections where firms are not immediately fined. The calibration avoids targeting parameters that could be affected by enforcement—such as focusing on firm behavior around inspections or on firms below the quota threshold—ensuring that the main parameters are not influenced by compliance decisions.

labor supply elasticity of disabled workers.

The empirical counterpart of equation 12 is:

$$\log\left(\textit{labor force disabled}_{r,t}\right) = \mu_d \log\left(w_{d,r,t}\right) + X_{r,t} + \mu_t + \mu_r + \epsilon_{r,t} \tag{13}$$

here, $\textit{labor force disabled}_{r,t}$ is the labor force participation of disabled workers in region r, and year t, μ_t is a time fixed effect that absorbs variations in $H(\pi, T)$, μ_r is a region fixed effect, and $\epsilon_{r,t}$ is the residual. The wages of disabled workers are instrumented by the exposure of different regions to the quota.

Table 9 shows the estimates of equation 13. The estimated elasticity varies from 0.41 to 0.29. In the main part of the paper, I assume it to be 0.4.

The labor supply elasticity estimate of 0.4 presented in Table 9 falls within the upper bound of long-run labor supply elasticities but remains lower than other estimates focused exclusively on disabled workers. For comparison, micro estimates of the labor supply elasticity for males typically range from 0 to 0.5 (Chetty et al. 2011, Peterman 2016), while estimates for females are generally higher, ranging from 0.5 to 1 (Bishop et al. 2009). In contrast, studies examining disabled workers have found substantially larger elasticities. For instance, Kostol and Mogstad (2014) estimate labor force participation elasticities between 7 and 9 using a tax credit as an exogenous shifter of labor supply. However, Kostol and Mogstad (2014) shows that the labor supply elasticity depends on the degree of severity of the disability. Therefore, a labor force participation elasticity of 0.4 is consistent with the quota leading individuals with less severe disabilities to join the labor market.

I calibrate the labor supply elasticity of non-disabled workers following the literature. According to Chetty et al. (2011), the micro estimates of the labor supply elasticity are around 0.1.

Government. The government's fiscal policy parameters include the payroll tax τ, disability insurance T, exogenous expenditure G, the quota for disabled workers $\bar{d}$, and the

Table 9: **Labor Supply Elasticity of Disabled Workers**

	(1) *log labor force disabled*	(2) *labor force disabled*	(3) *labor force disabled*	(4) *labor force disabled*	(5) *labor force disabled*
$\log(w_d)$	0.419***	0.347***	0.405***	0.390***	0.297***
	(0.0673)	(0.0786)	(0.0619)	(0.0861)	(0.0871)
Observations	1159	1146	1159	1159	1146
Controls	Baseline	State-Year FE	Firm Size Std.	Occupation Distribution	All

Notes: This table reports the labor supply elasticity of disabled workers estimated using equation 13. The wage of disabled workers is instrumented with the exposure to the quota, defined in 3. Column 1 presents the baseline specification described in equation 4. Column 2 adds state-year fixed effects as a control. Column 3 adds initial average firm size and the standard deviation of firm size interacted with year. Column 4 adds the initial share of 1-digit occupations interacted with year. Column 5 includes all the previous controls. The standard errors are clustered at the microregion level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

share of firms that comply with the quota, θ.

To calibrate τ, I match the ratio of fiscal revenue to GDP in Brazil, which is 0.32. T is set to match the average income of non-working disabled individuals in 2010, which was R$ 250. The exogenous expenditure G is determined as the residual between revenue from the payroll tax τ and spending on disability insurance T. Finally, $\bar{d}$ is calibrated to match with the quota for disabled workers:

$$\bar{d}(n+d) = \begin{cases} 0, \text{ if } n+d \in [0,100) \\ 0.02\left(d+n\right), \text{ if } n+d \in [100,200) \\ 0.03\left(d+n\right), \text{ if } n+d \in [200,500) \\ 0.04\left(d+n\right), \text{ if } n+d \in [500,1000) \\ 0.05\left(d+n\right), \text{ if } n+d \in [1000,\infty) \end{cases} \tag{14}$$

As previously discussed, many firms do not comply with the quota for disabled workers. Reports from the DEO indicate that only 34% of firms meet the quota before an inspection. To reflect this, I set $\theta = 0.34$.

Production Parameters. I calibrate α, the degree of decreasing returns to scale, following de Souza (2022), who estimates a production function for Brazil using standard methods in the literature. The elasticity of substitution across tasks, λ, is calibrated to zero following Acemoglu and Restrepo (2020).

Firm Heterogeneity. Each firm j belongs to a sector $s(j)$, and I calibrate the distribution Γ to match the firm size distribution within each sector. For simplicity, I assume that κ_j remains constant within a sector and that TFP follows a log-normal distribution:

$$\log(z_j) \sim N\left(\mu_{z,s(j)}, \sigma_{z,s(j)}\right)$$

I calibrate $\mu_{z,s(j)}$ and $\sigma_{z,s(j)}$ to match the mean and variance of firm size for firms with fewer than 95 workers in 2010. Since the model does not account for firms' compliance decisions regarding the quota, I cannot directly target the full firm size distribution, as the model should not generate it. However, given wages, the distribution of firms that are well below the quota threshold should remain unaffected, making them better calibration targets.

Disabled Worker Productivity. I calibrate the productivity of disabled workers, captured by the parameter κ_j, to match the estimated effect of inspections on firm size. If κ_j is high—meaning disabled workers are significantly less productive than non-disabled workers—firms face a higher cost of compliance, leading them to shrink in response to inspections. Conversely, if κ is low—indicating that disabled workers are nearly as productive as non-disabled workers—compliance costs are minimal, and inspections should have little to no effect on firm size.

To calibrate κ_j, I generate the same variation observed in the data within the model and estimate the effect of inspections using the same empirical strategy applied to the real data. For each sector s, I draw a sample of firms with more than 100 workers. These firms are then inspected and forced to satisfy the quota for disabled worker. The change in total employment from this variation corresponds to the effect of an inspection. In practice, I estimate on the model:

$$\beta_{s,model}(\kappa_s) = E\left(\log(m_{j,unconstrained}) - \log(m_{j,constrained}) | s(j) = s, \kappa_s\right)$$

where $m_{j,unconstrained}$ is the total number of workers in firm j when it is not constrained to satisfy the quota and $m_{j,constrained}$ is employment when it is forced to satisfy the quota.

Table C.28 shows the estimated parameters and the fit of the model. The model reproduces well the firm size distribution and the effect of an inspection.[34]

Summary of Identification and Non-Targeted Moments. Table 10 summarizes the calibrated and identified model parameters. Table C.28, in the Appendix, presents the estimated parameters governing the firm size distribution and the relative productivity of disabled workers across sectors, which were calibrated targeting moments of the firm size distribution and the effect of inspections on firm size. The model provides a good fit to all targeted moments.

Table C.29 shows the fit of the model on non-targeted moments. The model accurately reproduces the share of firms with fewer than 100 workers and those with 100 to 200 workers, despite not explicitly targeting these moments. It also closely matches the average firm size within each bracket of the quota and the hiring patterns of disabled workers across different firm sizes. However, as is common in Hopenhayn (1992)-type models, the fit is worse at the upper end of the firm size distribution (Jaimovich et al. 2023).

8 Quantitative Result

In this section, I show that the quota for disabled workers increases the welfare of workers with disabilities. However, because disabled workers have lower productivity in some sectors, enforcing the quota distorts firm hiring decisions, reducing firm size and welfare for non-disabled workers. If, instead of a quota, the government subsidized employment of disabled

[34] In the data, there are sectors in which only a small fraction of firms are inspected, such as agriculture and extractive. To reduce the variance of the targeted moments, the targetted effect of an inspection is grouped in four large sectors: tradables, high-skill services, low-skill services, and others.

Table 10: **Summary of Identification and Calibration**

Parameter	Description	Calibration Method	Source	Value
		Labor Supply Elasticity		
μ_d	Labor supply elasticity of disabled workers	Using the quota as instrument for wages in 12	Table 9	0.4
μ_n	Labor supply elasticity of non-disabled workers	Literature	Chetty et al. (2011)	0.1
		Production		
α	degree of decreasing returns to scale	Literature	de Souza (2022)	0.7577
λ	elasticity of substitution across tasks	Literature	Acemoglu and Restrepo (2020)	0
		Government		
τ	payroll taxes	Tax revenue as share of GDP	National Treasury	0.3229
T	disability insurance	Income of disabled workers outside of the labor force	2010 Census	250
G	exogenous expenditure of the gov	Difference between revenue and expenditure with disability insurance	Calibration	4.38E+10
$\bar{d}(.)$	quota for disabled workers	Quota for disabled workers in Brazil		Equation 14
		Firm Heterogeneity		
$\mu_{z,s}$	Average of firm's productivity	Match average firm size of firms with less than 95 workers	Table C.28	Table C.28
$\sigma_{z,s}$	Variance of firms's productivity	Match variance of firm size of firms with less than 95 workers	Table C.28	Table C.28
		Productivity of Disabled Workers		
κ_s	Sector specific productivity of disabled workers	Match effect of quota inspections by sector	Table C.28	Table C.28

workers, overall welfare would increase because disabled workers could select into the sectors where they are relatively more productive.

8.1 Effect of the Quota for Disabled Workers

Counterfactual: changes in enforcement and payroll taxes. In the baseline calibration, I assume that only a fraction of firms comply with the quota for disabled workers. In the following counterfactual exercises, I assume this fraction is either zero, which corresponds to no quota, or one, which corresponds to full enforcement of the quota. In each scenario, the government adjusts the payroll tax to balance the budget.

The quota increases employment of workers with disabilities at the cost of lower production. Table 11 compares the benchmark economy with the counterfactual scenario without a quota for disabled workers and the one with full enforcement. The results in Table 11 show that the quota succeeds in increasing disabled-worker employment but reduces government revenue and overall economic activity.

Table 11 shows that the economy without a quota for disabled workers has higher GDP and larger firms than the baseline or the full enforcement economies. This occurs because disabled workers, on average, are less productive than non-disabled workers. Consequently, when firms are compelled to hire disabled workers, their marginal costs rise, leading to smaller firms with lower production. Firms attempt to mitigate these effects by cutting their size, which reduces the number of disabled workers they must hire.

Nonetheless, the quota for disabled workers successfully increases the labor force participation of disabled workers. Table 11 shows that, with full enforcement, disabled workers' labor force participation would increase by 33.9%.

According to Table 11, the quota for disabled workers forces the government to raise payroll taxes. The quota has two opposing effects on the government's budget. On one hand, it lowers disability insurance costs by increasing disabled workers' labor force participation, which could reduce payroll taxes. On the other hand, it decreases payroll revenue from non-disabled workers. Because the drop in payroll revenue outweighs the savings in disability insurance, the government has to raise the marginal tax rate τ by 1.08% in the economy with full enforcement. Consequently, the quota does not reduce the overall cost of disability insurance.

Table 11: **Effect of the Quota for Disabled Workers**

	(1) Baseline	(2) No Quota	$\frac{(2)-(1)}{(1)}$ Percentage Change	(3) Full Enforcement	$\frac{(3)-(1)}{(1)}$ Percentage Change
			Production and Firms		
GDP Per Capita	1022.61	1025.4	0.27%	1010.65	-1.17%
Avg. Firm Size	8.424	8.425	0.01%	8.417	-0.08%
Hire Disabled Workers	0.139%	1.000%	617.92%	0.180%	29.47%
τ (Tax Rate)	32.29%	32.21%	-0.26%	32.64%	1.08%
			Labor Market		
w_n (Non-Disabled Wage)	1382.1	1385.85	0.27%	1363.05	-1.38%
w_d (Disabled Wage)	1460.46	1370.59	-6.15%	3641.47	149.34%
Disabled Labor Force	27.47%	26.67%	-2.91%	36.78%	33.90%
Non-Disabled Labor Force	74.15%	74.16%	0.01%	74.10%	-0.07%

Notes: This table shows the effect of different quota policies on aggregate outcomes. The first Column represents the baseline scenario, the second Column represents an economy without a quota for disabled workers, and Column 3 represents a scenario where all firms are required to satisfy the quota. GDP and wages are in 2010 Brazilian Reais. Avg. firm size is in number of workers.

Utilitarian welfare function. To calculate the welfare of different policies, I assume that the government uses an utilitarian welfare function assigning equal weight to each individual:

$$W(\theta) = \lambda_d E\left[u_i\left(c_d^i(\theta), l_d^i(\theta)|\theta\right)\right] + (1-\lambda_d)E\left[u_i\left(c_n^i(\theta), l_n^i(\theta)|\theta\right)\right]$$

where θ is the share of firms that are required to respect the quota for disabled workers, $(c_d^i(\theta), l_d^i(\theta))$ are the equilibrium consumption and labor supply decision of disabled workers when a fraction θ of firms satisfy the quota. Equivalently, $(c_n^i(\theta), l_n^i(\theta))$ is the consumption and labor supply of non-disabled workers. The utility functions u are defined in 6.

I present welfare gains in terms of consumption equivalent variation (CEV). This measure represents the increase in consumption we would need to provide households so that they become indifferent between the benchmark economy and the counterfactual economy. The consumption equivalent variation for a quota enforcement given by θ is

$$CEV(\theta) = 100 * \exp\left(W(\theta) - W^{benchmark}\right) - 1$$

where $W^{benchmark}$ is the welfare in the benchmark economy.

The quota benefits disabled workers but decreases welfare. Table 12 reports the welfare impact of the quota for disabled workers, expressed in consumption equivalent terms. The second Column shows that disabled workers would give up 1.44% of consumption to keep the quota for disabled workers as is in the baseline economy. A quota increases the demand for disabled workers, which in turn increases their wage and consumption. The quota raises the demand for disabled workers, leading to higher wages and consumption. Since the wage gains more than offset the disutility from increased labor force participation, disabled workers are better off under the quota policy.

In contrast, non-disabled workers would pay 0.031% of their consumption to avoid the quota. Overall, removing the quota would increase welfare by 0.026%. For the quota to raise aggregate welfare, the government would need to value disabled workers 5.9 times more than non-disabled workers.[35]

Table 12: **Welfare Effect of Alternative Policies**

	No Quota	**Full Enforcement**	**Optimal Subsidy**
Disabled	-1.444%	28.701%	4.080%
Non-Disabled	0.031%	-0.093%	0.019%
Economy	0.026%	-0.002%	0.034%

Notes: This table shows the welfare gain from different policies in consumption-equivalent terms. Each Column reports the increase in average consumption that would make households indifferent between the baseline equilibrium and the new one.

[35] Assuming that the government uses the welfare function given by $\psi\lambda_d E\left[u^d\left(c^i_d(\theta), l^i_d(\theta)|\theta\right)\right] + (1 - \lambda_d)E\left[u^n\left(c^i_n(\theta), l^i_n(\theta)|\theta\right)\right]$, where ψ is the weight on disabled workers. The quota would increase welfare only if $\psi \geq 5.9$.

8.2 Effect of a Subsidy for Disabled Workers

Counterfactual: subsidy for disabled workers. In this subsection, I study the effect of a subsidy for disabled workers. For that, I assume that enforcement of the quota is kept constant at the baseline level, while the government imposes a different payroll tax on disabled workers. The tax on non-disabled workers then adjusts to keep the government budget balanced.

Lower taxes for disabled workers increases welfare. Table 13 shows that the optimal tax on disabled workers is a subsidy of 10.33%, i.e., a payroll tax of 12.62% rather than the baseline tax of 32.2%. Two main factors push for a lower tax on disabled workers: the deadweight loss from taxing them and the role of disability insurance. Because disabled workers have a higher labor supply elasticity, as noted in section 7, taxing them creates a larger deadweight loss than taxing non-disabled workers. Consequently, a social planner would generally choose a higher tax on non-disabled workers rather than on disabled workers. In addition, by subsidizing disabled workers to enter the labor force, the government reduces disability insurance costs and can lower taxes on non-disabled workers. Moreover, because disabled workers can sort into sectors where they have a stronger comparative advantage, their average productivity becomes higher than it would be under a stricter quota.

Table 13 shows that lower taxes for disabled workers increase GDP and firm size. The subsidy prompts disabled workers to join the labor market in sectors where they are relatively more productive, which raises total output. Additionally, the subsidy substantially increases disabled workers' labor force participation, increasing it by 8.6% relative to the baseline economy. These results show that a subsidy for hiring disabled workers is a viable alternative to a quota.

Table 13: **Effect of Lower Taxes for Disabled Workers**

	(1) **Baseline**	(2) **Optimal Tax**	$\frac{(2)-(1)}{(1)}$ **Percentage Change**
		Taxes	
Tax on Disabled	32.29%	12.62%	-60.92%
Tax on Non-Disabled	32.29%	32.21%	-0.25%
		Production and Firms	
GDP	1022.61	1025.51	0.28%
Avg. Firm Size	8.424	8.426	0.02%
		Labor Market	
w_n (Non-Disabled Wage)	1382.1	1385.81	0.27%
w_d (Disabled Wage)	1460.46	1368.76	-6.28%
Disabled Labor Force	27.47%	29.83%	8.60%
Non-Disabled Labor Force	74.15%	74.16%	0.01%

Notes: This table presents the effect of an optimal subsidy for disabled workers on taxation, production, firms, and labor markets. GDP and wages are in 2010 Brazilian Reais. Avg. firm size is in number of workers.

9 Conclusion

In this paper, I use a model and data to evaluate the employment and welfare effects of a quota for disabled workers. I develop a model to study the labor market for disabled workers and the impact of a quota on firms. In this model, disabled and non-disabled workers must choose between participating in the labor force or staying outside of it. Disabled workers outside the labor force receive disability insurance. Firms produce by performing a range of tasks that can be carried out by either disabled or non-disabled workers, with disabled workers being relatively less productive at certain tasks.

The impact of the quota on the economy depends on two key parameters: the productivity and the labor supply elasticity of disabled workers. The productivity of disabled workers captures how costly it is for firms to hire them. The labor supply elasticity measures the extent to which disabled workers' wages must increase to induce them into joining the workforce.

Using variation from inspections of the quota for disabled workers, I show that the quota for disabled workers leads firms to reduce their size while increasing their hiring of disabled workers, suggesting that disabled workers have lower productivity. Moreover, I show that labor markets more exposed to the quota for disabled workers had a larger increase in the labor force participation of disabled workers but higher unemployment of non-disabled workers.

Calibrating the model to match the empirical estimates, I show that a quota for disabled workers decreases welfare and employment. Because disabled workers have low productivity, the quota increases the marginal cost of firms and decreases production. Overall, I find large negative effects of the quota on firm size and welfare.

Alternatively, I show that a subsidy for disabled workers can increase welfare and employment. By subsidizing disabled workers, the government can decrease expenditure on disability insurance and reduce overall taxation. Disabled workers would then select into employment in sectors where they are more productive.

References

Acemoglu, D. and P. Restrepo (2020): "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 128, 2188–2244.

Aghion, P., A. Bergeaud, and J. V. Reenen (2023): "The Impact of Regulation on Innovation," *American Economic Review*, 113, 2894–2936.

Almunia, M. and D. Lopez-Rodriguez (2018): "Under the Radar: The Effects of Monitoring Firms on Tax Compliance," *American Economic Journal: Economic Policy*, 10, 1–38.

Amirapu, A. and M. Gechter (2020): "Labor Regulations and the Cost of Corruption: Evidence from the Indian Firm Size Distribution," *The Review of Economics and Statistics*, 102, 34–48.

Bachas, P., R. N. Fattal Jaef, and A. Jensen (2019): "Size-dependent tax enforcement and compliance: Global evidence and aggregate implications," *Journal of Development Economics*, 140, 203–222.

Barnay, T., E. Duguet, C. L. Clainche, and Y. Videau (2019): "An evaluation of the 1987 French Disabled Workers Act: better paying than hiring," *The European Journal of Health Economics*, 20, 597–610.

Berlinski, S. and J. Gagete-Miranda (2024): "Enforcement Spillovers under Different Networks: The Case of Quotas for Persons with Disabilities in Brazil," .

Bishop, K., B. Heim, and K. Mihaly (2009): "Single Women's Labor Supply Elasticities: Trends and Policy Implications," *ILR Review*, 63, 146–168.

Caicedo, S., M. Espinosa, and A. Seibold (2022): "Unwilling to Train?—Firm Responses to the Colombian Apprenticeship Regulation," *Econometrica*, 90, 507–550.

Cardoso, A. and T. Lage (2005): "A inspeção do trabalho no Brasil," *Dados*, 48, 451–490.

Cattaneo, M. D., M. Jansson, and X. Ma (2018): "Manipulation testing based on density discontinuity," *Stata Journal*, 18, 234–261.

——— (2019): "lpdensity: Local Polynomial Density Estimation and Inference," Papers 1906.06529, arXiv.org.

Chetty, R., A. Guren, D. Manoli, and A. Weber (2011): "Are Micro and Macro Labor Supply Elasticities Consistent? A Review of Evidence on the Intensive and Extensive Margins," *American Economic Review*, 101, 471–475.

Corseuil, C. H. L., R. Almeida, and P. Carneiro (2012): "Inspeção do trabalho e evolução do emprego formal no Brasil," Texto para Discussão 1688, Instituto de Pesquisa Econômica Aplicada (Ipea), Brasília.

Dabla-Norris, M. E., L. Jaramillo, F. Lima, and A. Sollaci (2018): "Size Dependent Policies, Informality and Misallocation," IMF Working Papers 2018/179, International Monetary Fund.

de Souza, G. (2022): "The Labor Market Consequences of Appropriate Technology," Working Paper Series WP 2022-53, Federal Reserve Bank of Chicago.

Duryea, S., C. Martínez, and R. Smith (2024): "Disability Employment Quotas: Effects of Laws and Nudges," .

García-Santana, M. and J. Pijoan-Mas (2014): "The reservation laws in India and the misallocation of production factors," *Journal of Monetary Economics*, 66, 193–209.

Garicano, L., C. Lelarge, and J. V. Reenen (2016): "Firm Size Distortions and the Productivity Distribution: Evidence from France," *American Economic Review*, 106, 3439–3479.

Goos, M., A. Manning, and A. Salomons (2014): "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, 104, 2509–26.

Gourio, F. and N. Roys (2014): "Size-dependent regulations, firm size distribution, and reallocation," *Quantitative Economics*, 5, 377–416.

Guner, N., G. Ventura, and X. Yi (2008): "Macroeconomic Implications of Size-Dependent Policies," *Review of Economic Dynamics*, 11, 721–744.

Hopenhayn, H. A. (1992): "Entry, Exit, and firm Dynamics in Long Run Equilibrium," *Econometrica*, 60, 1127–1150.

Jaimovich, N., S. J. Terry, and N. Vincent (2023): "The Empirical Distribution of Firm Dynamics and Its Macro Implications," Working Paper 31337, National Bureau of Economic Research.

Kostol, A. R. and M. Mogstad (2014): "How Financial Incentives Induce Disability Insurance Recipients to Return to Work," *American Economic Review*, 104, 624–55.

Kreko, J. and A. Telegdy (2022): "The Effects of a Disability Employment Quota When Compliance Is Cheaper than Defiance," *IZA Discussion Papers*, No. 15726.

Lalive, R., J.-P. Wuellrich, and J. Zweimüller (2013): "Do Financial Incentives Affect Firms' Demand For Disabled Workers?" *Journal of the European Economic Association*, 11, 25–58.

Migalhas (2025): "Empresa é condenada a cumprir cota de PcD e pagar multa de R$ 500 mi," .

Ministério do Trabalho (2018): "Caracterização das Deficiências: Orientações para fins de cumprimento do art. 93 da Lei nº 8.213/91," .

Mori, Y. and N. Sakamoto (2018): "Economic consequences of employment quota system for disabled people: Evidence from a regression discontinuity design in Japan," *Journal of the Japanese and International Economies*, 48, 1–14.

Peck, J. R. (2017): "Can Hiring Quotas Work? The Effect of the Nitaqat Program on the Saudi Private Sector," *American Economic Journal: Economic Policy*, 9, 316–47.

Peterman, W. B. (2016): "RECONCILING MICRO AND MACRO ESTIMATES OF THE FRISCH LABOR SUPPLY ELASTICITY," *Economic Inquiry*, 54, 100–120.

Ribeiro, M. A. and R. Carneiro (2009): "A inclusão indesejada: as empresas brasileiras face à lei de cotas para pessoas com deficiência no mercado de trabalho," *Organizações Sociedade*, 16, pp. 117–136.

Szerman, C. (2023): "The Labor Market Effects of Disability Hiring Quotas," *Working Paper*.

Transite (2016): "Empresas multadas por descumprirem Lei de Cotas para Pessoas com Deficiência," Accessed: 2025-03-15.

Tribunal Regional do Trabalho da 3ª Região (2022): "Empresa prova dificuldade na contratação de trabalhadores com deficiência e tem auto de infração anulado," .

Vermelho (2018): "Empresas tentam burlar contratação de trabalhadores com deficiência," .

Viollaz, M. (2018): "Are labour inspections effective when labour regulations vary according to the size of the firm? Evidence from Peru," *International Labour Review*, 157, 213–242.

A Quota for Disabled Workers

A.1 Definition of Disabilities

Physical : "complete or partial alteration of one or more segments of the human body, resulting in impairment of physical function, presenting as paraplegia, paraparesis, monoplegia, monoparesia, tetraplegia, tetraparesia, triplegia, triparesia, hemiplegia, hemiparesis, ostomy, amputation or absence of limb, cerebral palsy, dwarfism, limbs with congenital or acquired deformity, except for aesthetic deformities and those that do not produce difficulties in the performance of duties";

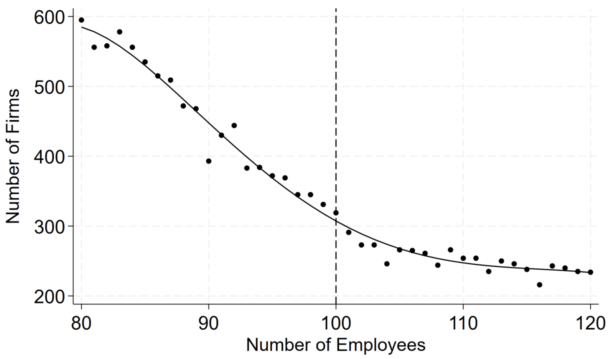
Auditive : partial or total bilateral loss of forty-one decibels (dB) or more, measured by audiogram at frequencies of 500HZ, 1,000HZ, 2,000Hz and 3,000Hz;

Visual : blindness, in which visual acuity is equal to or less than 0.05 at best eye, with the best optical correction; low vision, which means visual acuity between 0.3 and 0.05 in the best eye, with the best optical correction; cases in which the sum of the visual field measure in both eyes is equal to or less than 60o; or the simultaneous occurrence of any of the conditions above;

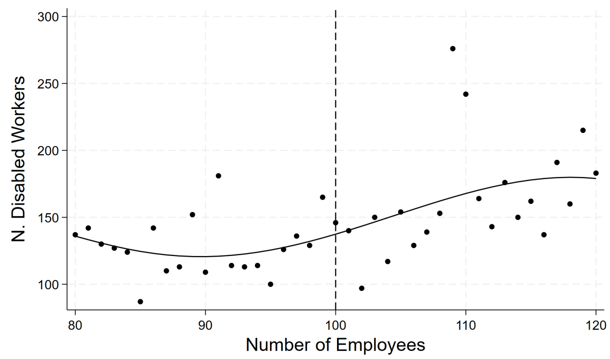
Cognitive : significantly lower than average intellectual functioning, with manifestation before the age of eighteen and limitations associated with two or more areas of adaptive skills, such as: communication, personal care, social abilities, health and security, academic faculties, leisure, work.

Figure A.1: **Distribution of Firms and Disabled Workers Around the 100 Discontinuity**

(a) **Distribution of Firms**



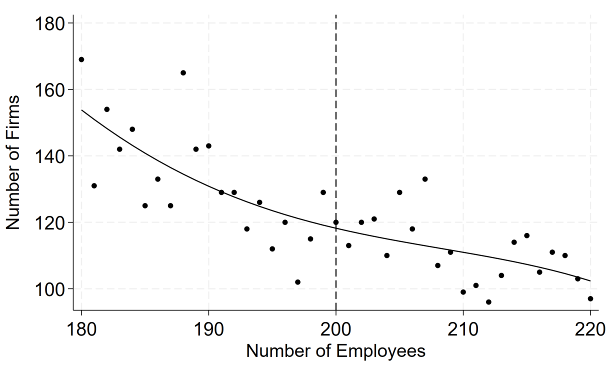
(b) **Number of Disabled Workers**



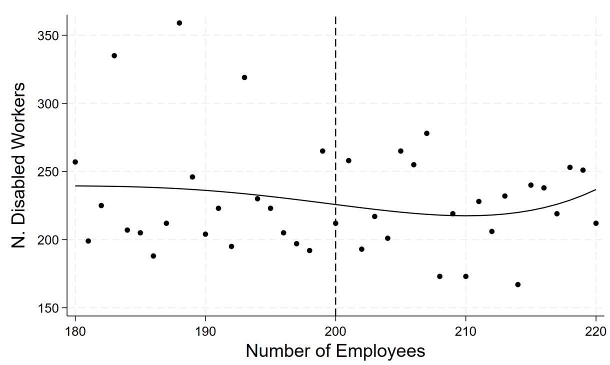
Notes: These figures plot the number of firms and the number of disabled workers for firms with between 80 and 120 employees. The vertical line at 100 marks the first discontinuity of the quota for disabled workers. In Figure (a), the x-axis represents total firm employment, and the y-axis shows the number of firms with that exact size in 2016. In Figure (b), the x-axis also represents firm size, while the y-axis displays the total number of disabled workers employed by firms of each size.

Figure A.2: **Distribution of Firms and Disabled Workers Around the 200 Discontinuity**

(a) **Distribution of Firms**



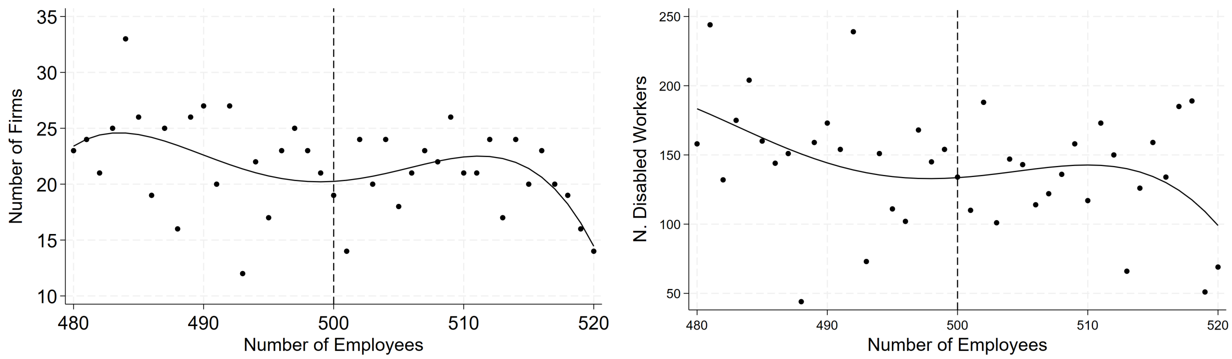
(b) **Number of Disabled Workers**



Notes: These figures plot the number of firms and the number of disabled workers for firms with between 180 and 220 employees. The vertical line at 200 marks the second discontinuity of the quota for disabled workers. In Figure (a), the x-axis represents total firm employment, and the y-axis shows the number of firms with that exact size in 2016. In Figure (b), the x-axis also represents firm size, while the y-axis displays the total number of disabled workers employed by firms of each size.

Figure A.3: **Distribution of Firms and Disabled Workers Around the 500 Discontinuity**

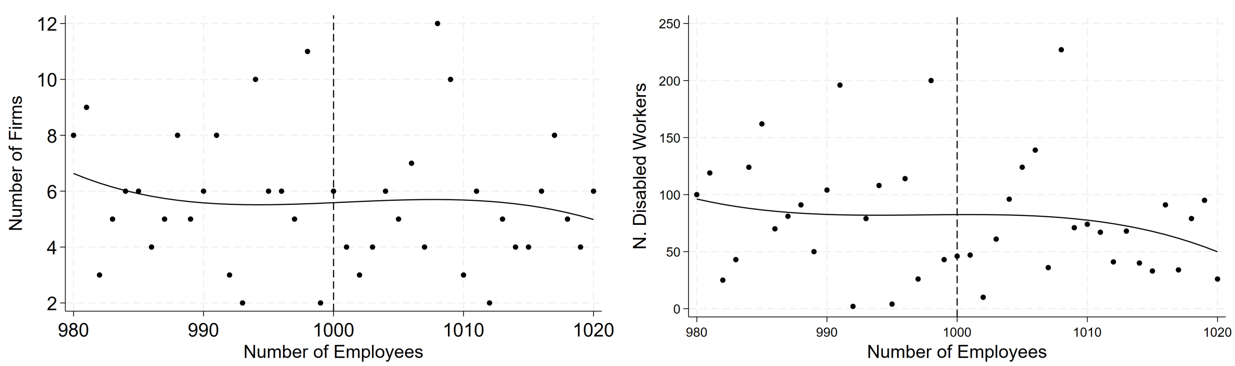
(a) **Distribution of Firms** (b) **Number of Disabled Workers**



Notes: These figures plot the number of firms and the number of disabled workers for firms with between 480 and 520 employees. The vertical line at 500 marks the second discontinuity of the quota for disabled workers. In Figure (a), the x-axis represents total firm employment, and the y-axis shows the number of firms with that exact size in 2016. In Figure (b), the x-axis also represents firm size, while the y-axis displays the total number of disabled workers employed by firms of each size.

Figure A.4: **Distribution of Firms and Disabled Workers Around the 1,000 Discontinuity**

(a) **Distribution of Firms** (b) **Number of Disabled Workers**



Notes: These figures plot the number of firms and the number of disabled workers for firms with between 980 and 1,020 employees. The vertical line at 1,000 marks the second discontinuity of the quota for disabled workers. In Figure (a), the x-axis represents total firm employment, and the y-axis shows the number of firms with that exact size in 2016. In Figure (b), the x-axis also represents firm size, while the y-axis displays the total number of disabled workers employed by firms of each size.

B Empirics

B.1 Effect of Disabled Quota on Firms

B.1.1 Comparison to General Labor Market Inspections

To isolate the impact of the quota from broader labor market enforcement, I rely on inspections conducted by the DEO, which exclusively enforces the quota for disabled workers. In contrast, Szerman (2023), in a paper published two years after this one, attempts to estimate the effect of the quota using general labor market inspections. Unlike DEO inspections, general labor inspections are often triggered by external complaints, judicial referrals, or major incidents. As a result, firms undergoing these inspections are more likely to be experiencing other labor-related issues, such as wage disputes or compliance failures, leading to endogeneity concerns. This correlation can explain why Szerman (2023) finds pre-trends in employment and no effect of inspections on firm size. In this section, I discuss the institutional framework of general labor market inspections and demonstrate that they fail key validity tests—such as those performed in Section 4.1.3—that DEO inspections successfully pass.

Firm characteristics predict general labor market inspections. Table B.2 underscores why it is crucial to restrict the analysis to DEO inspections. In this table, I replicate a regression of firm-level outcomes on a dummy variable that takes the value one if the firm will be inspected by a general labor market inspector within the next five years. Unlike DEO officials, these inspectors systematically target firms that have larger workforces, pay higher wages, and operate multiple establishments. These correlations are statistically significant across all horizons. Consequently, the timing of general labor market inspections correlates with firm dynamics, which potentially leads to endogeneity.

General labor market inspections are triggered by direct complaints, judicial referrals, or accidents. General labor market inspections are systematically correlated with firm dynamics because they are often triggered by direct complaints (from workers, unions, or judicial authorities), judicial referrals, or high-profile events such as serious accidents (Cardoso and Lage 2005, Corseuil et al. 2012). As a result, larger or faster-growing companies that attract more attention—due to a bigger workforce, higher wage levels, the presence of multiple establishments, or a greater volume of legal disputes—are more likely to be inspected first. Therefore, the timing of a general labor market inspection correlates not only with firm growth but also with other confounders such as labor lawsuits, labor union strikes, or accidents.

Differently from general labor market inspections, inspections by the DEO are not triggered by external agents. As described before, inspectors select firms based on their employment status as available in RAIS. This is why, as Table B.1 illustrates, there is no correlation between the DEO's inspections and labor market outcomes.

General labor market inspections correlate with other labor infractions. In contrast, general labor market inspections cannot isolate the effect of the quota for disabled workers. Table B.6 shows the correlation between fines for breaking the disabled workers' quota and other labor market regulations in general inspections. For this table, I use the same matching procedure described in Section 4.1.1, but the event is a fine for breaking the quota in a general labor inspection. Table B.6 reveals that broad inspections often uncover both quota infractions and additional workplace violations, notably severance-payment failures and bookkeeping issues. This pattern arises partly because firms involved in labor lawsuits, which are usually motivated by late payment, are more likely to face general labor inspections, which tend to expose multiple violations (Cardoso and Lage 2005, Corseuil et al. 2012). Thus, unlike DEO inspections, general labor market inspections cannot cleanly isolate the effect of quota enforcement at the firm level.

B.1.2 Task Content Variables

This subsection describes the construction of variables measuring task content at the firm level. I construct a measure of mismatch between disabled workers and their occupations in different firms. To construct the mismatch measure, I first create measures of physical, auditive, visual, and cognitive task content for each occupation, i.e., the intensity of different occupations on tasks related to the major disabilities covered by the quota for disabled workers.

For each occupation, I calculate the physical task content as the average of O*NET questions after normalization on “Arm-Hand Steadiness”, “Manual Dexterity”, “Finger Dexterity”, “Control Precision”, “Multilimb Coordination”, “Response Orientation”, “Rate Control”, “Static Strength”, “Explosive Strength”, “Dynamic Strength”, “Trunk Strength”, “Stamina”, “Extent Flexibility”, “Dynamic Flexibility”, “Gross Body Coordination”, “Gross Body Equilibrium”, “Performing General Physical Activities”, “Handling and Moving Objects”, “Controlling Machines and Processes”, and “Operating Vehicles, Mechanized Devices, or Equipment”.

For each occupation, the auditive task content is the average of O*NET questions after normalization on “Oral Comprehension”, “Oral Expression”, “Response Orientation”, “Hearing Sensitivity”, “Auditory Attention”, “Sound Localization”, “Speech Recognition”, “Speech Clarity”, “Persuasion”, “Negotiation”, “Instructing”, “Service Orientation”, “Getting Information”, “Interpreting the Meaning of Information for Others”, “Communicating with Supervisors, Peers, or Subordinates”, “Communicating with Persons Outside Organization”, “Establishing and Maintaining Interpersonal Relationships”, “Assisting and Caring for Others”, “Selling or Influencing Others”, “Resolving Conflicts and Negotiating with Others”, and “Performing for or Working Directly with the Public”.

For each occupation, the visual task content is the average of O*NET questions after normalization of “Spatial Orientation”, “Visualization”, “Control Precision”, “Multilimb Coordination”, “Response Orientation”, “Rate Control”, “Near Vision”, “Far Vision”, “Visual Color Discrimination”, “Night Vision”, “Peripheral Vision”, “Depth Perception”, “Glare Sensitivity”, and “Getting Information”.

The cognitive task content is the average of O*NET questions after normalization on “Fluency of Ideas”, “Originality”, “Problem Sensitivity”, “Deductive Reasoning”, “Inductive Reasoning”, “Information Ordering”, “Category Flexibility”, “Memorization”, “Reading Comprehension”, “Active Listening”, “Writing”, “Speaking”, “Mathematics”, “Science”, “Critical Thinking”, “Active Learning”, “Learning Strategies”, “Monitoring”, “Complex Problem Solving”, “Judging the Qualities of Things, Services, or People”, “Processing

Information", "Evaluating Information to Determine Compliance with Standards", "Analyzing Data or Information", "Making Decisions and Solving Problems", "Thinking Creatively", "Updating and Using Relevant Knowledge", "Developing Objectives and Strategies", "Scheduling Work and Activities", and "Organizing, Planning, and Prioritizing Work".

The mismatch between a disabled worker i and occupation o is given by

$$mismatch_{o,i} = \begin{cases} \text{physical task content}_o & \text{if } i \text{ has a physical disability} \\ \text{auditive task content}_o & \text{if } i \text{ has a hearing disability} \\ \text{visual task content}_o & \text{if } i \text{ has a visual disability} \\ \text{cognitive task content}_o & \text{if } i \text{ has a cognitive disability} \end{cases}$$

The mismatch between disabled workers and their occupation in firm j is the average of $mismatch_{o,i}$ across disabled workers.

B.1.3 Random Inspection Time

Table B.1: **Firm Characteristics and Probability of First Inspection in the Future**

	(1)	(2)	(3)	(4)	(5)
	$\mathbb{I}\{$*first inspection t+1*$\}$	$\mathbb{I}\{$*first inspection t+2*$\}$	$\mathbb{I}\{$*first inspection t+3*$\}$	$\mathbb{I}\{$*first inspection t+4*$\}$	$\mathbb{I}\{$*first inspection t+5*$\}$
log(# workers)	0.0263	0.0249	-0.0126	0.0278	-0.000821
	(0.241)	(0.391)	(0.708)	(0.483)	(0.984)
log(avg. wage)	0.0458**	-0.0371	0.0218	-0.00761	-0.0107
	(0.040)	(0.240)	(0.536)	(0.828)	(0.784)
log(yrs. educ.)	-0.00962	-0.0106	-0.102	0.0227	-0.0446
	(0.882)	(0.896)	(0.300)	(0.830)	(0.724)
shr. male	-0.00141	-0.239**	0.0667	-0.0679	0.320**
	(0.987)	(0.028)	(0.564)	(0.632)	(0.035)
log(# establishments)	-0.0136	0.00581	-0.0111	-0.0243	0.0500*
	(0.363)	(0.756)	(0.612)	(0.336)	(0.070)
log(# municipalities)	-0.0244	0.0229	-0.00635	-0.0851	-0.0155
	(0.512)	(0.558)	(0.899)	(0.151)	(0.766)
Observations	19656	18340	17838	17237	16447
R^2	0.615	0.609	0.592	0.570	0.571

Notes: This table presents the estimates from a regression of firm characteristics on a dummy variable indicating whether a firm will be inspected by the DEO within the next one to five years. Standard errors are clustered at the firm level. The regression includes several fixed effects to account for variation in inspection criteria over time: firm fixed effects, sector-year fixed effects, city-year fixed effects, and quota percentage-year fixed effects. The sample is restricted to firms that have ever been inspected, up to the year of their inspection, ensuring that the correlation doesn't come from inspections affecting firm dynamics. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.2: **Firm Characteristics and Probability of First Inspection in the Future**

	(1)	(2)	(3)	(4)	(5)
	$\mathbb{I}\{$*first inspection t+1*$\}$	$\mathbb{I}\{$*first inspection t+2*$\}$	$\mathbb{I}\{$*first inspection t+3*$\}$	$\mathbb{I}\{$*first inspection t+4*$\}$	$\mathbb{I}\{$*first inspection t+5*$\}$
log(# workers)	0.0418***	0.0183***	0.00489***	-0.00111**	-0.00234***
	(0.000)	(0.000)	(0.000)	(0.031)	(0.000)
log(avg. wage)	0.0126***	0.00225**	-0.000960	-0.000737	-0.00273**
	(0.000)	(0.032)	(0.381)	(0.516)	(0.018)
log(yrs. educ.)	-0.00864***	-0.00490***	-0.00141	0.000316	0.00117
	(0.000)	(0.000)	(0.232)	(0.795)	(0.343)
shr. male	-0.00727***	0.00125	-0.000439	0.00194	0.00131
	(0.000)	(0.311)	(0.738)	(0.154)	(0.345)
log(# establishments)	0.0570***	0.0396***	0.0264***	0.0185***	0.00953***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(# municipalities)	0.000783	-0.0255	-0.0171	-0.0627***	-0.0252
	(0.969)	(0.212)	(0.407)	(0.003)	(0.220)
Observations	3508705	3462123	3363008	3274287	3170676
R^2	0.394	0.329	0.291	0.281	0.281

Notes: This table presents the estimates from a regression of firm characteristics on a dummy variable indicating whether a firm will receive a general labor market inspection within the next one to five years. Standard errors are clustered at the firm level. The regression includes firm fixed effects, sector-year fixed effects, city-year fixed effects, and quota percentage-year fixed effects to control for systematic differences in inspection criteria over time. These controls help account for variations in firm characteristics that may influence the likelihood of inspection. The sample is restricted to firms that have ever been inspected, up to the year of their inspection, ensuring comparability within the relevant group. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B.1.4 Exogeneity

Table B.3: **Comparison Between Treatment and Control**

Variable	Treatment	Control	Difference	P-Value
Founding Year	1,977.657	1,976.925	-0.732	0.147
N. Disabled Workers	11.554	13.825	2.272	0.103
N. Workers	810.513	929.300	118.788*	0.080
Wage	2,518.573	2,580.512	61.939	0.399
Avg. Work Week Hours	40.914	40.822	-0.092	0.685
Hourly Wage	71.128	73.991	2.864	0.400
Years of Education	11.210	11.333	0.122	0.172
Disabled Mismatch	-0.192	-0.179	0.014	0.674
Auditive Task Content	-0.018	0.018	0.035	0.145
Cognitive Task Content	-0.376	-0.348	0.028	0.175
Physical Task Content	0.067	0.043	-0.024	0.264
Visual Task Content	-0.073	-0.070	0.004	0.884
Observations	755	973	1,728	

Notes: This table shows summary statistics for matched treatment and control firms in the year prior to the first inspection of treatment firms. Task content variables are defined in Section B.1.2. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.4: **Exogeneity Tests**

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{I}\{$*Ever Had Fed. Loan*$\}$	$\mathbb{I}\{$*Fed. Loan*$\}$	$\mathbb{I}\{$*Ever Had Public Procurement*$\}$	$\mathbb{I}\{$*Public Procurement*$\}$	*log(Public Procurement)*	$\mathbb{I}\{$*Ever Campaign Contribution*$\}$
$\mathbb{I}\{Inspection\}$	0.00194	-0.00458	-0.0129	-0.0109	0.458	0.000742
	(0.00494)	(0.00366)	(0.0109)	(0.00867)	(0.285)	(0.000912)
Observations	9918	9918	9918	9918	616	9918
R^2	0.867	0.395	0.876	0.623	0.869	0.952
Mean Dep. Var	0.024	0.008	0.173	0.084	12.745	0.046
Mean Ind. Var	0.18	0.18	0.18	0.18	0.18	0.18

Notes: Using specification 1, this table presents the correlation between inspections of the quota for disabled workers and other policies. In Column (1), the outcome variable is a dummy indicating whether the firm has ever received a loan from BNDES, the Brazilian National Development Bank. BNDES is a major state-owned financial institution that provides subsidized loans to firms. It is also well known for its history of extending favorable credit to firms with political connections to the government. Column (2) captures whether the firm received a BNDES loan in the current period. Column (3) examines whether the firm has ever signed a public procurement contract with the federal government, and Column (4) indicates whether such a contract was signed in the current period. Column (5) reports the log value of the public procurement agreement, and Column (6) is a dummy indicating whether the firm has made a campaign contribution in the past. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.5: **Correlation Between Inspections by the DEO and other Labor Market Infractions**

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{I}\{$*Infraction Except Quota*$\}$	$\mathbb{I}\{$*Informal*$\}$	$\mathbb{I}\{$*Labor Tax*$\}$	$\mathbb{I}\{$*Overtime*$\}$	$\mathbb{I}\{$*Payroll Delay*$\}$	$\mathbb{I}\{$*Failure to Pay Severance*$\}$
$\mathbb{I}\{Inspection\}$	0.0268	-0.00144	0.0101	-0.00521	0.000165	0.00190
	(0.0205)	(0.00948)	(0.00981)	(0.0144)	(0.0101)	(0.00891)
Observations	8679	8679	8679	8679	8679	8679
R^2	0.588	0.461	0.535	0.527	0.465	0.512
Mean Dep. Var	0.303	0.031	0.036	0.104	0.044	0.029
Mean Ind. Var	0.18	0.18	0.18	0.18	0.18	0.18

Notes: This table presents the correlation between inspections for the disabled workers quota and various labor market infractions using model 1. In Column (1), the outcome variable is a dummy equal to one if the firm committed any labor market infraction other than a violation of the disabled workers quota. Column (2) considers whether the firm was fined for hiring informal workers, while Column (3) examines fines for failure to pay labor taxes. Column (4) captures whether the firm was fined for requiring employees to work overtime without proper authorization. Column (5) assesses fines for late payroll payments, and Column (6) indicates whether the firm was fined for failure to pay severance pay. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.6: **Correlation Between Quota Infractions in General Labor Inspections and other Labor Market Infractions**

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{I}\{Infraction\ Except\ Quota\}$	$\mathbb{I}\{Ever\ Had\ Infraction\ Except\ Quota\}$	$\mathbb{I}\{Failure\ to\ Pay\ Severance\}$	$\mathbb{I}\{Ever\ Failure\ to\ Pay\ Severance\}$	$\mathbb{I}\{Faulty\ Book\ Keeping\}$	$\mathbb{I}\{Ever\ Faulty\ Book\ Keeping\}$
$\mathbb{I}\{GeneralInspection\}$	0.0498**	0.0421*	0.0227*	0.0484***	0.00912	0.0551**
	(0.0250)	(0.0224)	(0.0135)	(0.0170)	(0.0161)	(0.0217)
Observations	5771	5771	5771	5771	5771	5771
R^2	0.624	0.825	0.445	0.809	0.534	0.842
Mean Dep. Var	0.434	0.660	0.047	0.118	0.095	0.227
Mean Ind. Var	0.15	0.15	0.15	0.15	0.15	0.15

Notes: Using specification 1, this table examines the correlation between quota infractions identified in general labor market inspections and other labor violations. The matching procedure follows the approach outlined in Section 4.1.1, with the key difference that firms are matched based on quota infractions detected in general labor inspections rather than DEO inspections. In Column (1), the outcome variable is a dummy indicating whether the firm committed a labor market infraction other than the quota violation for disabled workers in the current period, while Column (2) captures whether the firm has ever committed such an infraction. Columns (3) and (4) assess whether the firm was fined for failing to pay the legally required severance payment, either in the current period or at any point in the past. Finally, Columns (5) and (6) indicate whether the firm failed to maintain appropriate labor tax records. Standard errors are clustered at the firm level. Significance levels are indicated as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B.1.5 Other Empirical Results

Table B.7: **Effect of Inspections of the Quota for Disabled Workers on the Hiring of Disabled Workers**

	(1) N. Disabled Workers	(2) $\mathbb{I}\{$*Physical Disability*$\}$	(3) $\mathbb{I}\{$*Hearing Disability*$\}$	(4) $\mathbb{I}\{$*Visual Disability*$\}$	(5) $\mathbb{I}\{$*Cognitive Disability*$\}$	(6) $\mathbb{I}\{$*Multiple Disabilities*$\}$
$\mathbb{I}\{Inspection\}$	6.868***	0.193***	0.113***	0.108***	0.113***	0.0328***
	(1.549)	(0.0160)	(0.0172)	(0.0182)	(0.0157)	(0.0114)
Observations	11336	11336	11336	11336	11336	11336
R^2	0.541	0.796	0.745	0.698	0.741	0.702
Mean Dep. Var	14.589	0.475	0.34	0.253	0.16	0.075
Mean Ind. Var	0.16	0.16	0.16	0.16	0.16	0.16

Notes: This table shows the effect of inspections of the quota for disabled workers on the hiring of disabled employees, estimated using model 1. In Column (1), the outcome variable is the total number of disabled workers employed by the firm. Column (2) is a dummy variable indicating whether the firm has at least one worker with a physical disability. Column (3) considers whether the firm employs at least one worker with a hearing disability, while Column (4) examines the presence of at least one worker with a visual disability. Column (5) captures whether the firm has at least one worker with a cognitive disability, and Column (6) indicates whether the firm employs at least one worker with multiple disabilities. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.8: **Effect of Inspections of the Quota for Disabled Workers on the Hiring of Disabled Workers**

	(1) *log(N. Physical Dis.)*	(2) *log(N. Hearing Dis.)*	(3) *log(N. Visual Dis.)*	(4) *log(N. Cognitive Dis.)*	(5) *log(N. Multiple Dis.)*
$\mathbb{I}\{Inspection\}$	0.180***	0.152*	0.00144	0.325**	0.349
	(0.0546)	(0.0811)	(0.0994)	(0.138)	(0.217)
Observations	5560	3975	2931	1889	824
R^2	0.839	0.842	0.751	0.860	0.853
Mean Dep. Var	1.85	1.401	0.843	1.015	0.573
Mean Ind. Var	0.16	0.16	0.16	0.16	0.16

Notes: This table shows the effect of inspections of the quota for disabled workers on the hiring of workers with disabilities, estimated using model 1. In Column (1), the outcome variable is the log of the number of workers with physical disabilities. Column (2) reports the log of the number of workers with hearing disabilities, while Column (3) considers the log of the number of workers with visual disabilities. Column (4) examines the log of the number of workers with cognitive disabilities, and Column (5) captures the log of the number of workers with multiple disabilities. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.9: **Effect of Inspections of the Quota for Disabled Workers on the Characteristics of Disabled Workers**

	(1) *log(Wage Disable)*	(2) *log(Hour Wage Disable)*	(3) *log(Yrs. Educ. Disable)*	(4) *log(Weekly Hour Disable)*
$\mathbb{I}\{Inspection\}$	-0.0242	-0.0400*	-0.00239	0.000662
	(0.0211)	(0.0223)	(0.00850)	(0.00478)
Observations	6377	6377	6374	6377
R^2	0.887	0.897	0.854	0.759
Mean Dep. Var	7.542	3.86	2.29	3.711
Mean Ind. Var	0.16	0.16	0.16	0.16

Notes: This table shows the effect of inspections of the quota for disabled workers on the characteristics of disabled employees, estimated using model 1. In Column (1), the outcome variable is the log of the average wage of disabled workers. Column (2) reports the log of the hourly wage of disabled workers. Column (3) examines the average years of education among disabled workers, while Column (4) is their average weekly hours of work. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.10: **Effect of Inspections of the Quota for Disabled Workers on the Tasks Performed by Disabled Workers**

	(1) *Physical Task*	(2) *Cognitive Task*	(3) *Abstract Routine*	(4) *Abstract Non-Routine*	(5) *Routine Manual*
$\mathbb{I}\{Inspection\}$	0.0474***	-0.0761***	0.0367**	-0.0747***	0.0444**
	(0.0183)	(0.0180)	(0.0185)	(0.0184)	(0.0185)
Observations	6361	6361	6361	6361	6361
R^2	0.872	0.811	0.879	0.797	0.877
Mean Dep. Var	0.077	-0.565	-0.041	-0.514	-0.005
Mean Ind. Var	0.16	0.16	0.16	0.16	0.16

Notes: This table shows the effect of inspections of the quota for disabled workers on the characteristics of disabled workers using model 1. In Column (1), the outcome variable is the physical task content, as defined in Section B.1.2. Column (2) reports the cognitive task content, also defined in Section B.1.2. *Abstract Routine* measures the extent of repetitive tasks that require minimal physical effort, following Goos et al. (2014), using ONET indicators such as "Operation Monitoring," "Operation and Control," and "Quality Control Analysis." *Abstract Non-Routine* captures the intensity of creative tasks, based on Goos et al. (2014), using ONET indicators including "Originality," "Critical Thinking," and "Active Learning." *Routine Manual* reflects the degree of repetitive manual tasks, constructed using ONET measures such as "Arm-Hand Steadiness," "Manual Dexterity," "Finger Dexterity," "Reaction Time," "Wrist-Finger Speed," and "Speed of Limb Movement." Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B.1.6 Robustness

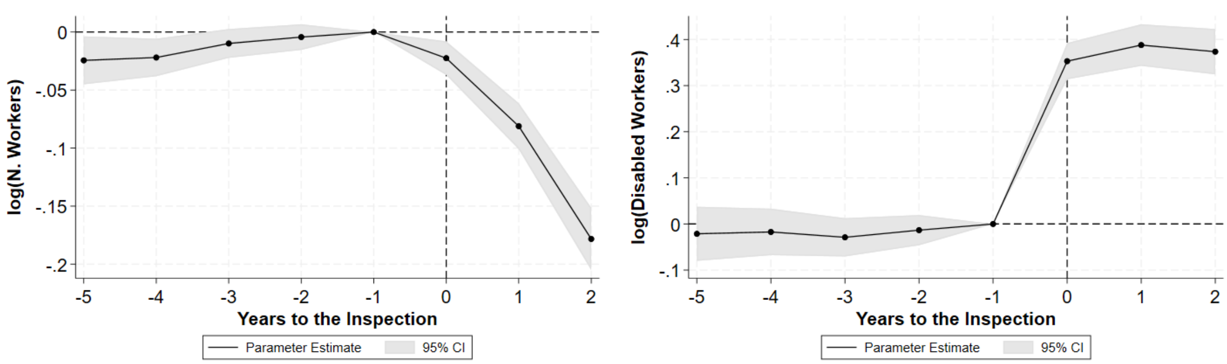
Table B.11: **Effect of Inspections of the Quota for Disabled Workers on Firms, with Matching Only on Firm Age**

	(1)	(2)	(3)	(4)	(5)	(6)
	log(N. Dis. Workers)	$\mathbb{I}\{\geq$ *One Dis. Worker*$\}$	$\mathbb{I}\{$*Satisfy Quota*$\}$	*log(N. Workers)*	*log(N. Not Dis. Workers)*	$\mathbb{I}\{$*Decrease Group Quota*$\}$
$\mathbb{I}\{Inspection\}$	0.403***	0.251***	0.213***	-0.0669***	-0.0741***	0.0385***
	(0.0213)	(0.00813)	(0.00750)	(0.00911)	(0.00913)	(0.00298)
N	74580	148176	148176	148176	148070	148176
R^2	0.798	0.628	0.468	0.899	0.895	0.130
Mean Dep. Var	1.439	0.508	0.229	5.536	5.525	0.029
Mean Ind. Var	0.07	0.07	0.07	0.07	0.07	0.07

Notes: This table shows the effect of inspections of the quota for disabled workers on firm outcomes using model 1. Treatment and control groups are matched only on firm age to account for differences in their position within the life cycle. *log(N. Dis. Workers)* represents the log of the number of disabled workers at the firm. $\mathbb{I}\{\geq$ *One Dis. Worker*$\}$ is a dummy variable equal to one if the firm has at least one disabled worker. $\mathbb{I}\{$*Satisfy Quota*$\}$ is a dummy equal to one if the firm complies with the quota for disabled workers. *log(N. Workers)* denotes the log of the total number of workers at the firm, while *log(N. Not Dis. Workers)* represents the log of the number of non-disabled workers. $\mathbb{I}\{$*Decrease Group Quota*$\}$ is a dummy equal to one if the firm reduces the percentage of disabled workers it is required to hire, i.e., if it decreases employment enough to go down a discontinuity of the quota. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure B.5: **Effect of Inspections on Firm Dynamics, with Matching Only on Age**

(a) **Number of Workers** (b) **Number of Non-Disabled Workers**



Notes: This figure plots the dynamic estimates of the effect of inspections of the quota for disabled workers according to model 2. Firms are matched on their age in the year before the inspection to account for differences in business life-cycle growth rates. In Figure B.5a, the variable of interest is the number of workers. In Figure B.5b, the variable of interest is the log of the number of non-disabled workers. Standard errors are clustered at the firm level.

Table B.12: **Effect of Inspections of the Quota for Disabled Workers with Matched-Pair-Year Fixed Effects**

	(1)	(2)	(3)
	log(N. Workers)	*log(N. Not Disabled Workers)*	*log(N. Disabled Workers)*
$\mathbb{I}\{Inspection\}$	-0.0302*	-0.0415**	0.203***
	(0.0160)	(0.0165)	(0.0624)
Sector-Year FE			
Munic-Year FE			
Match-Year FE	X	X	X
Observations	9928	9928	5202
R^2	0.981	0.979	0.868
Mean Dep. Var	5.985	5.972	2.406
Mean Ind. Var	0.16	0.16	0.16

Notes: This table shows the effect of inspections of the quota for disabled workers on firm outcomes using model 1 and different controls. Columns (1) to (3) include matched-pair-year fixed effects as additional controls. *log(N. Workers)* represents the log of the total number of workers at the firm. *log(N. Not Disabled Workers)* captures the log of the number of non-disabled workers, while *log(N. Disabled Workers)* denotes the log of the number of disabled workers employed by the firm. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.13: **Effect of Inspections of the Quota for Disabled Workers with Sector-Year and Municipality-Year FE**

	(1)	(2)	(3)
	log(N. Workers)	*log(N. Not Disabled Workers)*	*log(N. Disabled Workers)*
$\mathbb{I}\{Inspection\}$	-0.0542**	-0.0583***	0.282***
	(0.0218)	(0.0218)	(0.0766)
Sector-Year FE	X	X	X
Munic-Year FE	X	X	X
Match-Year FE			
Observations	7968	7968	4254
R^2	0.987	0.985	0.949
Mean Dep. Var	5.985	5.972	2.406
Mean Ind. Var	0.16	0.16	0.16

Notes: This table shows the effect of inspections of the quota for disabled workers on firm outcomes using model 1 and different controls. Columns (1) to (3) include sector-year and municipality-year fixed effects as additional controls. *log(N. Workers)* represents the log of the total number of workers at the firm. *log(N. Not Disabled Workers)* captures the log of the number of non-disabled workers, while *log(N. Disabled Workers)* denotes the log of the number of disabled workers employed by the firm. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.14: **Effect of Inspections of the Quota for Disabled Workers with Matched-Pair-Year, Sector-Year, and City-Year Fixed Effects**

	(1) *log(N. Workers)*	(2) *log(N. Not Disabled Workers)*	(3) *log(N. Disabled Workers)*
$\mathbb{I}\{Inspection\}$	-0.0225	-0.0266	0.328***
	(0.0242)	(0.0242)	(0.0973)
Sector-Year FE	X	X	X
Munic-Year FE	X	X	X
Match-Year FE	X	X	X
Observations	6072	6072	2928
R^2	0.993	0.992	0.970
Mean Dep. Var	5.985	5.972	2.406
Mean Ind. Var	0.16	0.16	0.16

Notes: This table shows the effect of inspections of the quota for disabled workers on firm outcomes using model 1 and different controls. Columns (1) to (3) include sector-year, municipality-year, and matched-group-year fixed effect as additional controls. *log(N. Workers)* represents the log of the total number of workers at the firm. *log(N. Not Disabled Workers)* captures the log of the number of non-disabled workers, while *log(N. Disabled Workers)* denotes the log of the number of disabled workers employed by the firm. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.15: **Effect of Inspections of the Quota for Disabled Workers, with Matching 2 Years Before Inspection**

	(1)	(2)	(3)
	log(N. Workers)	*log(N. Not Disabled Workers)*	*log(N. Disabled Workers)*
$\mathbb{I}\{Inspection\}$	-0.0489***	-0.0567***	0.300***
	(0.0116)	(0.0117)	(0.0394)
Observations	32811	32794	15035
R^2	0.931	0.928	0.854
Mean Dep. Var	5.548	5.538	1.814
Mean Ind. Var	0.15	0.15	0.15
N. Firms	4090	4090	2751
Years Aft. Inspection	3	3	3
Matched Years	2	2	2

Notes: This table shows the effect of inspections of the quota for disabled workers on firm outcomes using model 1. For each inspected firm, a control firm is matched based on the two years leading up to the inspection. Firms are matched on age, sector, number of disabled workers, and total number of workers. The control firms are inspected at least three years after the treatment firms. *log(N. Workers)* is the log of the total number of workers employed by the firm. *log(N. Not Disabled Workers)* is the log of the number of non-disabled workers at the firm, while *log(N. Disabled Workers)* is the log of the number of disabled workers employed by the firm. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.16: **Effect of Inspections of the Quota for Disabled Workers, with Matching 5 Years Before Inspection**

	(1)	(2)	(3)
	log(N. Workers)	*log(N. Not Disabled Workers)*	*log(N. Disabled Workers)*
$\mathbb{I}\{Inspection\}$	-0.0380	-0.0540*	0.351***
	(0.0320)	(0.0320)	(0.128)
Observations	2440	2440	1873
R^2	0.971	0.970	0.834
Mean Dep. Var	6.811	6.792	3.256
Mean Ind. Var	0.18	0.18	0.18
N. Firms	305	305	265
Years Aft. Inspection	3	3	3
Matched Years	5	5	5

Notes: This table shows the effect of inspections of the quota for disabled workers on firm outcomes using model 1. For each inspected firm, a control firm is matched based on the five years leading up to the inspection. Firms are matched on age, sector, number of disabled workers, and total number of workers. The control firms are inspected at least three years after the treatment firms. *log(N. Workers)* is the log of the total number of workers employed by the firm. *log(N. Not Disabled Workers)* is the log of the number of non-disabled workers at the firm, while *log(N. Disabled Workers)* is the log of the number of disabled workers employed by the firm. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.17: **Effect of Inspections of the Quota for Disabled Workers with Control Firms Inspected at Least 4 Years Later**

	(1)	(2)	(3)
	log(N. Workers)	*log(N. Not Disabled Workers)*	*log(N. Disabled Workers)*
$\mathbb{I}\{Inspection\}$	-0.0410***	-0.0550***	0.115
	(0.0155)	(0.0163)	(0.0708)
Observations	7974	7973	4303
R^2	0.975	0.968	0.848
Mean Dep. Var	5.979	5.965	2.41
Mean Ind. Var	0.17	0.17	0.17
N. Firms	996	996	732
Years Aft. Inspection	4	4	4
Matched Years	3	3	3

Notes: This table shows the effect of inspections of the quota for disabled workers on firm outcomes using model 1. For each inspected firm, a control firm is matched based on the two years leading up to the inspection. Firms are matched on age, sector, number of disabled workers, and total number of workers. The control firms are inspected at least four years after the treatment firms. *log(N. Workers)* is the log of the total number of workers employed by the firm. *log(N. Not Disabled Workers)* is the log of the number of non-disabled workers at the firm, while *log(N. Disabled Workers)* is the log of the number of disabled workers employed by the firm. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.18: **Effect of Inspections of the Quota for Disabled Workers with Control Firms Inspected at Least 6 Years Later**

	(1)	(2)	(3)
	log(N. Workers)	*log(N. Not Disabled Workers)*	*log(N. Disabled Workers)*
$\mathbb{I}\{Inspection\}$	-0.0185	-0.0187	-0.317***
	(0.0243)	(0.0245)	(0.116)
Observations	2680	2680	1384
R^2	0.985	0.984	0.843
Mean Dep. Var	5.858	5.844	2.382
Mean Ind. Var	0.19	0.19	0.19
N. Firms	334	334	244
Years Aft. Inspection	6	6	6
Matched Years	3	3	3

Notes: This table shows the effect of inspections of the quota for disabled workers on firm outcomes using model 1. For each inspected firm, a control firm is matched based on the two years leading up to the inspection. Firms are matched on age, sector, number of disabled workers, and total number of workers. The control firms are inspected at least six years after the treatment firms. *log(N. Workers)* is the log of the total number of workers employed by the firm. *log(N. Not Disabled Workers)* is the log of the number of non-disabled workers at the firm, while *log(N. Disabled Workers)* is the log of the number of disabled workers employed by the firm. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.19: **Effect of Inspections of the Quota for Disabled Workers, with Matching on Additional Variables**

	(1) *log(N. Disabled Workers)*	(2) $\mathbb{I}\{$*At Least One Disabled Worker*$\}$	(3) $\mathbb{I}\{$*Satisfy Quota*$\}$	(4) *log(N. Workers)*	(5) *log(N. Not Disabled Workers)*	(6) $\mathbb{I}\{$*Decrease Group Quota*$\}$
$\mathbb{I}\{Inspection\}$	0.241**	0.0893**	0.0909*	-0.0214	-0.0274	0.0121
	(0.116)	(0.0373)	(0.0473)	(0.0397)	(0.0396)	(0.0162)
Observations	938	1303	1303	1303	1301	1303
R^2	0.910	0.896	0.821	0.993	0.993	0.536
Mean Dep. Var	2.741	0.761	0.173	6.444	6.425	0.019
Mean Ind. Var	0.18	0.18	0.18	0.18	0.18	0.18

Notes: This table shows the effect of inspections of the quota for disabled workers on firm outcomes using model 1. Each inspected firm is matched to another firm inspected at least three years later based on hourly wage, number of establishments, share of high-school dropouts, sector, employment, number of disabled workers, and age in the three years before the inspection. *log(N. Workers)* is the log of the total number of workers employed by the firm. *log(N. Not Disabled Workers)* is the log of the number of non-disabled workers at the firm, while *log(N. Disabled Workers)* is the log of the number of disabled workers employed by the firm. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

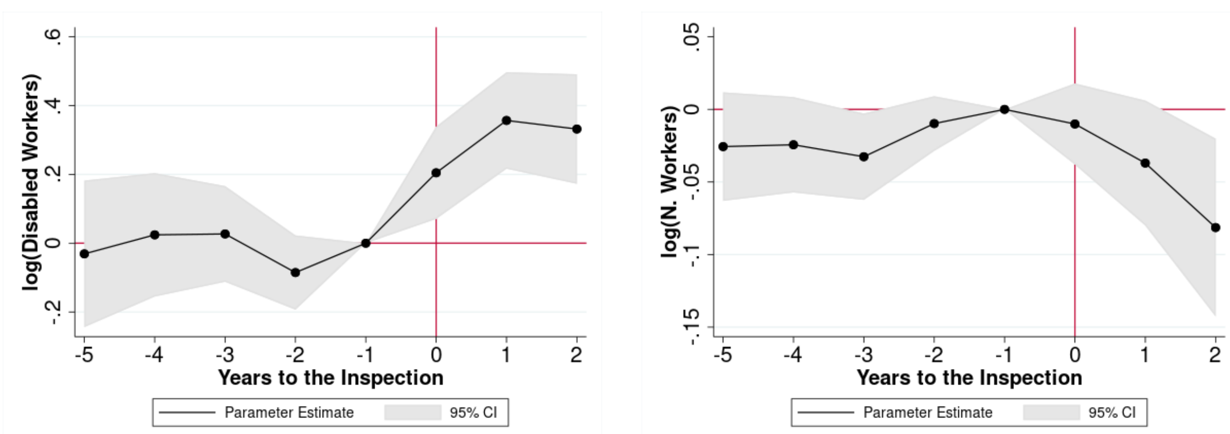
Table B.20: **Effect of Inspections of the Quota for Disabled Workers Matching on Information Available to Inspectors**

	(1)	(2)	(3)	(4)	(5)	(6)
	log(N. Workers)	*log(N. Not Disabled Workers)*	*log(N. Disabled Workers)*	*log(N. Workers)*	*log(N. Not Disabled Workers)*	*log(N. Disabled Workers)*
$\mathbb{I}\{Inspection\}$	-0.0260	-0.0327*	0.341***	-0.0386*	-0.0445**	0.320***
	(0.0196)	(0.0196)	(0.0723)	(0.0207)	(0.0206)	(0.0713)
Observations	8376	8375	4463	7072	7071	3944
R^2	0.971	0.970	0.890	0.965	0.965	0.902
Mean Dep. Var	5.954	5.942	2.352	5.968	5.955	2.309
Mean Ind. Var	0.17	0.17	0.17	0.17	0.17	0.17
N. Firms	1047	1047	770	884	884	668
Years to Inspection	3	3	3	3	3	3
Matched Years	3	3	3	3	3	3
Lag Year	2	2	2	3	3	3

Notes: This table shows the effect of inspections of the quota for disabled workers on firm outcomes using model 1, employing a matching strategy based on lagged outcomes. For each inspected firm, a control firm is matched based on outcomes from 5 to 2 years before the inspection (Columns 1 to 3) and from 6 to 3 years before the inspection (Columns 4 to 6). *log(N. Workers)* is the log of the total number of workers employed by the firm. *log(N. Not Disabled Workers)* is the log of the number of non-disabled workers at the firm, while *log(N. Disabled Workers)* is the log of the number of disabled workers employed by the firm. Standard errors are clustered at the firm level. Significance levels are denoted as follows: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure B.6: **Effect of Inspections Matching on 3-Year Lagged Outcomes**

(a) **Number of Disabled Workers** (b) **Number of Workers**



Notes: This figure plots the dynamic estimates of the effect of inspections of the quota for disabled workers according to model 2. Firms inspected at time 0 are matched to firms inspected at least 3 years later based on outcomes from 5 to 3 years before the inspection. In Figure B.6a, the variable of interest is the number of disabled workers. In Figure B.6b, the variable of interest is the log of the number of non-disabled workers. Standard errors are clustered at the firm level.

Table B.21: **Effect of Inspections of the Quota for Disabled Workers on the Number of Disabled Workers**

	(1) *log(N. Dis. Workers)*	(2) $\mathbb{I}\{\geq$ *One Dis. Worker*$\}$	(3) *N. Dis. Workers*	(4) *log(N. Dis. Workers+1)*	(5) *IHS(N. Dis. Workers+1)*	(6) *Shr. Dis. Workers*
$\mathbb{I}\{Inspection\}$	0.203***	0.228***	6.933***	0.407***	0.503***	0.00735***
	(0.0624)	(0.0182)	(1.803)	(0.0409)	(0.0479)	(0.00133)
Observations (N)	5202	9928	9928	9928	9928	9928
R^2	0.868	0.876	0.699	0.926	0.927	0.635
Mean Dep. Var	2.406	0.547	14.589	1.401	1.706	0.012
Mean Ind. Var	0.16	0.16	0.16	0.16	0.16	0.16

Notes: This table shows the effect of inspections of the quota for disabled workers on the number of disabled workers using model 1. *log(N. Dis. Workers)* is the log of the number of disabled workers employed by the firm, $\mathbb{I}\{\geq$ *One Dis. Worker*$\}$ is a dummy variable equal to one if the firm employs at least one disabled worker, *N. Dis. Workers* is the total number of disabled workers at the firm, *log(N. Dis. Workers+1)* is the log-plus-one transformation of the number of disabled workers, *IHS(N. Dis. Workers)* is the inverse hyperbolic sine transformation of the number of disabled workers, and *Shr. Dis. Workers* is the share of disabled workers in the firm's total workforce. Standard errors are in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.22: **Effect of Inspections of the Quota for Disabled Workers on the Likelihood to be Fined According to the Distance to the Discontinuity and Disability Mismatch**

	(1)	(2)	(3)	(4)
	$\mathbb{I}\{Fine\}$	*log(Fine Value)*	$\mathbb{I}\{Fine\}$	*log(Fine Value)*
	Closer to Discontinuity		*Highest Disability Mismatch*	
$\mathbb{I}\{Inspection\}$	0.139***	1.280***	0.178***	1.987***
	(0.0185)	(0.176)	(0.0332)	(0.381)
Observations	2309	2309	1056	1056
	Far from Discontinuity		*Lowest Disability Mismatch*	
$\mathbb{I}\{Inspection\}$	0.163***	1.805***	0.154***	1.771***
	(0.0233)	(0.269)	(0.0368)	(0.438)
Observations	2888	2888	1160	1160

Notes: This table shows the effect of inspections of the quota for disabled workers on the probability and size of fines, using model 1. As discussed in Section 2, receiving a fine from a labor inspector does not imply immediate payment, as fines are first litigated within the Ministry of Labor and subsequently in the Labor Court. In Columns (1) and (2), the top panel reports the effect of inspections on firms in the bottom quartile of distance to the closest lower quota discontinuity in the year before the inspection; the bottom panel shows results for firms in the top quartile. This selection is made among both treatment and control firms. In Columns (3) and (4), the top panel includes only firms in the top quartile of disability mismatch in the year prior to inspection, while the bottom panel includes only firms in the bottom quartile. The disability mismatch of firms is defined in Section B.1.2. $\mathbb{I}\{Fine\}$ is a dummy equal to one if the firm was fined by a labor inspector. *log(Fine Value)* is the logarithm of the fine amount plus one. Standard errors are clustered at the firm level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.23: **Effect of Inspections on Employment of Disabled Workers According to How Often They Were Labeled as a Disabled Worker**

	(1) *log(N. Always Dis. Workers)*	(2) I{$\geq$ *One Always Dis. Worker*}	(3) *N. Always Dis. Workers*	(4) *log(N. Always Once Workers)*	(5) I{$\geq$ *One Once Dis. Worker*}	(6) *N. Once Dis. Workers*
$\mathbb{I}\{Inspection\}$	0.204***	0.158***	1.747***	0.165***	0.0254**	10.26***
	(0.0702)	(0.0193)	(0.436)	(0.0285)	(0.0120)	(3.059)
Observations	4269	9928	9928	8574	9928	9928
R^2	0.879	0.843	0.929	0.973	0.786	0.975
Mean Dep. Var	1.504	0.468	4.398	2.486	0.893	57.681
Mean Ind. Var	0.16	0.16	0.16	0.16	0.16	0.16

Notes: This table presents the effect of inspections on the employment of disabled workers using different disability definitions. Columns (1)-(3) report employment measures for workers who have consistently been classified as disabled throughout their entire employment history. Columns (4)-(6) present employment measures for workers who have been classified as disabled at least once in their employment history. Standard errors are in parentheses. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B.1.7 Bunching After Inspections

In Section 4, I show that firms near the lower discontinuities of the quota are more likely to downsize after an inspection of the quota for disabled workers. This finding is consistent with firms bunching at the quota's discontinuities. In this section, I provide evidence that, after an inspection, the mass of firms at the quota discontinuity is statistically larger.

However, an important caveat is that the sample size for this test is relatively small. The sample in Section 4 has 621 inspected firms. For comparison, Garicano et al. (2016)—in their seminal study on bunching in France—analyzed about 400 firms in each bin around the discontinuity, with a total sample of roughly 10,000 firms. Therefore, confidence intervals are large.[36]

To test whether firms adjust their size to avoid the quota, I use the manipulation test developed by Cattaneo et al. (2018) and Cattaneo et al. (2019). Their method estimates a polynomial function of the firm size distribution on each side of the discontinuity. If the two estimated functions are statistically different at zero, it suggests that firms actively adjust their size in response to the quota.

For this test, I restrict the sample to treatment firms two years after an inspection. As a comparison, I also perform the same test on matched control firms two years after the inspection of their matched treatment to get a benchmark to determine whether any observed discontinuity is specifically driven by the quota enforcement or simply reflects broader firm dynamics unrelated to the policy.

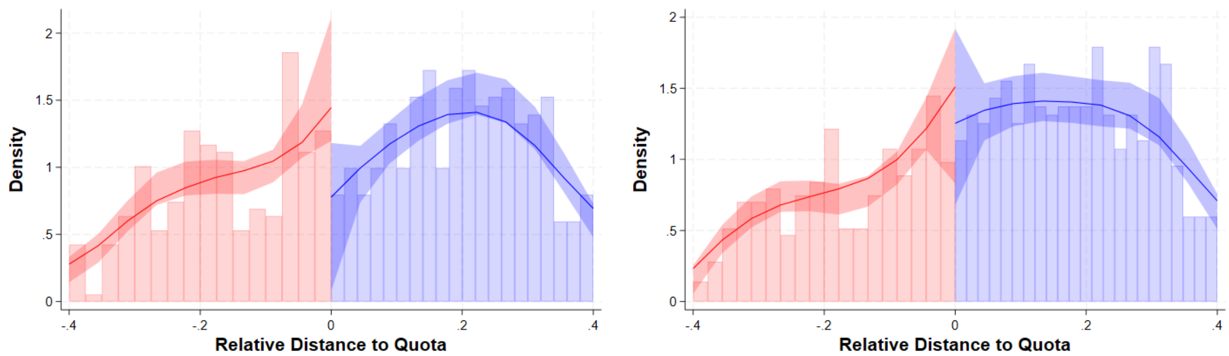
Figure B.7 plots the firm size density along with a second-order polynomial fit in each side. The x-axis contains the percentage distance to the nearest discontinuity, while the y-axis shows the density of firms. The shaded area represents a 90% confidence interval and the lines are a second degree polynomial estimated in each side of the discontinuity. The figure shows that, two years after an inspection, the number of firms just below the discontinuity is statistically larger than the number just above it, indicating that firms are bunching to reduce their quota obligations. For comparison, Figure B.7b shows the same

[36] Two factors contribute to the lower density of firms around the discontinuity. First, the quota threshold begins at 100 employees, which is much higher than the cutoffs analyzed in other papers. Second, the sample is restricted to inspected firms. Because inspections tend to target larger firms, many firms in the sample are far from the discontinuity.

analysis for control firms. In this case, there is no statistically significant difference in firm density around zero, suggesting that the observed bunching effect among treated firms is driven by quota enforcement rather than broader firm dynamics.

Figure B.7: **Distribution of Firms Around Quota Discontinuities**

(a) **Treatment** (b) **Control**



Notes: This figure plots the density manipulation test proposed by Cattaneo et al. (2018) and Cattaneo et al. (2019). In Figure B.7a, the x-axis is the percentage distance to the nearest discontinuity, while the y-axis shows the density of firms. The shaded area represents a 90% confidence interval and the lines are a second-degree polynomial estimated on each side of the discontinuity. In Figure B.7a, the sample is limited to the matched treatment firms 2 years after the inspection. In Figure B.7b, the sample is limited to the matched control firms 2 years after the inspection of their matched treatment counterpart.

B.2 Effect on the Labor Market

B.2.1 Robustness

Table B.24: **Effect of Quota for Disabled Workers on the Labor Market**

	(1) *Employment Rate*	(2) *Employment Rate*	(3) *Employment Rate*	(4) *Employment Rate*	(5) *Employment Rate*	(6) *Employment Rate*	(7) *Employment Rate*
				Disabled and Non-Disabled Workers			
exposure	-0.0201***	-0.0207***	-0.0185***	-0.0108***	-0.0272***	-0.00839**	-0.00754**
	(0.00384)	(0.00472)	(0.00488)	(0.00338)	(0.00492)	(0.00348)	(0.00370)
Observations	2211	2211	2211	1671	1667	1664	1664
R^2	0.961	0.961	0.961	0.971	0.964	0.981	0.984
# Regions	557	557	557	557	557	556	556
				Disabled Workers			
exposure	0.0442***	0.0488***	0.0553***	0.0290***	0.0291***	0.0244***	0.0221**
	(0.00659)	(0.00633)	(0.00697)	(0.00570)	(0.00783)	(0.00546)	(0.0105)
Observations	1615	1615	1615	1615	1603	1609	1597
R^2	0.865	0.866	0.867	0.879	0.869	0.891	0.898
# Regions	539	539	539	539	535	537	533
Controls	Baseline	Firm Size Distr.	Polynomial Firm Size Distr.	Occupation Shr.	Sectoral GDP	State-Year FE	All

Notes: This table reports the effect of exposure to the quota for disabled workers on the employment rate according to model 4. The first panel includes all workers, disabled and non-disabled; the second panel includes only workers with disabilities. Column (1) presents the baseline results. Column (2) controls for the average and standard deviation of employment per firm in 1990 interacted with year dummies. Column (3) includes the level and square root of the average and standard deviation of employment per firm in 1990 interacted with year dummies. Column (4) controls for the share of workers in different 1-digit occupation codes in 1991 interacted with year dummies. Column (5) includes sectoral GDP of each region in 1991 interacted with year dummies. Column (6) adds state-year fixed effects. Column (7) includes all controls listed. The data for the first panel are from the Brazilian Census of 1980, 1991, 2000, and 2010. The data for the second panel are from the Brazilian Census of 1991, 2000, and 2010. Standard errors are clustered at the microregion level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.25: **Effect of Quota for Disabled Workers on the Labor Market using Different Exposure Measures**

	(1) *Employment Rate*	(2) *Labor Force*	(3) *Unemployment Rate*	(4) *Shr. SSC Contrib.*	(5) *log(Income)*
			Baseline		
exposure	-0.0201***	-0.000432	0.00883***	-0.0128**	0.0283***
	(0.00384)	(0.00210)	(0.00263)	(0.00570)	(0.00604)
			Unique Region Firms		
exposure	-0.0141***	-0.00501***	0.00608***	-0.0186***	0.0216***
	(0.00264)	(0.00169)	(0.00196)	(0.00407)	(0.00510)
			Log Number of Disabled Workers Required		
exposure	-0.0101***	0.000480	0.00503	-0.0257***	0.0201***
	(0.00380)	(0.00199)	(0.00340)	(0.00372)	(0.00749)
			Disabled Normalized		
exposure	-0.0120+	0.00284	0.00707*	-0.00662	0.0101
	(0.00727)	(0.00428)	(0.00361)	(0.00455)	(0.0152)

Notes: This table reports the effect of exposure to the quota for disabled workers on the labor market according to model 4 using different exposure measures. The first panel uses the baseline exposure defined in 3. The second panel calculates the exposure measure using only firms that have all their establishments in one region. The third panel uses the log of the number of disabled workers required by the quota in 1999 as the exposure measure. The fourth panel normalizes the number of disabled workers required by the quota by the number of disabled workers in each region. The data come from the Brazilian Census of 1980, 1991, 2000, and 2010. Standard errors are clustered at the microregion level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.26: **Effect of Quota for Disabled Workers on the Labor Market of Disabled Workers using Different Exposure Measures**

	(1) *Employment Rate*	(2) *Labor Force*	(3) *Unemployment Rate*	(4) *Work-Age Retirement*	(5) *Shr. SSC Contrib.*	(6) *log(Income)*
			Baseline			
exposure	0.0442***	0.0309***	-0.0369***	-0.0306***	0.113***	0.209***
	(0.00659)	(0.00338)	(0.00610)	(0.00341)	(0.0127)	(0.0228)
			Unique Region Firms			
exposure	0.0277***	0.0167***	-0.0223***	-0.0202***	0.0667***	0.128***
	(0.00632)	(0.00342)	(0.00573)	(0.00359)	(0.0115)	(0.0233)
			Log Number of Disabled Workers Required			
exposure	0.0292***	0.0195***	-0.0220***	-0.0193***	0.0929***	0.182***
	(0.00713)	(0.00408)	(0.00630)	(0.00486)	(0.00960)	(0.0209)
			Disabled Normalized			
exposure	0.0424***	0.0297***	-0.0356***	-0.0218**	0.119***	0.240***
	(0.00814)	(0.00668)	(0.00738)	(0.0108)	(0.0166)	(0.0304)

Notes: This table reports the effect of exposure to the quota for disabled workers on labor market outcomes using model 4 with alternative exposure measures. The first panel uses the baseline exposure defined in equation 3. The second panel calculates the exposure measure using only firms that have all their establishments in one region. The third panel measures exposure as the log of the number of disabled workers required by the quota in 1999. The fourth panel normalizes the number of disabled workers required by the quota by the number of disabled workers in each region. The data come from the Brazilian Censuses of 1980, 1991, 2000, and 2010. Standard errors are clustered at the microregion level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.27: **Effect of Quota for Disabled Workers on the Labor Market of Disabled Workers using Different Definitions of Disability**

	(1) *Employment Rate*	(2) *Unemployment Rate*	(3) *Labor Force*	(4) *Work-Age Retirement*	(5) *Shr. SSC Contrib.*	(6) *log(Income)*	(7) *log(N. Disabled)*
exposure	0.0454***	0.0310***	-0.0362***	-0.0306***	0.123***	0.198***	-0.00689
	(0.00644)	(0.00353)	(0.00595)	(0.00336)	(0.0129)	(0.0235)	(0.0228)
Observations	1516	1664	1516	1664	1575	1571	1667
R^2	0.888	0.796	0.895	0.825	0.838	0.986	0.976
# Regions	506	555	506	555	526	524	556

*Notes:*This table reports the effect of exposure to the quota for disabled workers on regional labor market outcomes of workers with auditory, visual, or cognitive disabilities, according to model 4. The variable of interest in Column 1 is the employment rate; in Column 2, the unemployment rate; in Column 3, the labor force participation rate; in Column 4, the share of retired individuals aged between 18 and 50; in Column 5, the number of workers making social security contributions; and**,** in the last Column, wages. The data come from the Brazilian Censuses of 1991, 2000, and 2010. The Census of 1980 does not include an identifier for disability. Standard errors are clustered at the microregion level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C Model

Table C.28: **Targeted Moments and Model Parameters**

	Parameters			*Average Firm Size*		*Variance of Firm Size*		*Effect of Inspections*	
	$\mu_{z,s}$	$\sigma_{z,s}$	κ_s	Model	Target	Model	Target	Model	Target
Agriculture	7.870	0.472	68.774	11.098	11.046	17.094	17.169	-0.019	-0.020
Extractive	7.836	0.380	119.809	9.209	9.130	14.177	14.238	-0.020	-0.020
Manufacturing	7.915	0.353	1.810	11.027	11.045	15.243	15.270	-0.012	-0.020
Utilities	7.901	0.345	17.610	10.474	10.384	14.617	14.578	-0.019	-0.023
Construction	8.119	0.389	44.399	18.507	18.451	20.913	20.910	-0.023	-0.023
Retail	7.923	0.381	32.691	11.745	11.652	16.426	16.451	-0.021	-0.023
Transportation	7.740	0.298	71.021	5.288	5.229	8.151	8.214	-0.023	-0.023
Hospitality	7.828	0.287	710.408	7.100	7.132	9.911	9.824	-0.045	-0.053
ICT	7.746	0.394	385.602	7.270	7.184	12.507	12.535	-0.054	-0.053
Prof. Services	7.769	0.353	418.943	7.040	6.965	11.477	11.535	-0.053	-0.053
Education	7.715	0.404	384.111	6.778	6.702	12.121	12.149	-0.054	-0.053
Others	7.749	0.352	442.531	6.564	6.507	10.908	10.974	-0.067	-0.066

Notes: This table presents sector-specific parameters, average firm size, variance of firm size, and the effects of inspections. The "Target" Columns represent the values in the data, while the "Model" Columns show the values generated by the model.

Table C.29: **Non-Targeted Moments**

	Shr. of Firms		*Avg. Number of Workers*		*Avg. N. Disabled Workers*	
Group	*Model*	*Data*	*Model*	*Data*	*Model*	*Data*
Less than 100 workers	98.74%	98.11%	6.85	6.88	0.00	0.01
Between 100 and 200 workers	0.78%	0.86%	121.52	139.66	0.68	0.81
Between 200 and 300 workers	0.47%	0.60%	291.79	310.79	6.96	2.71
Between 300 and 500 workers	0.07%	0.23%	631.44	700.30	17.89	6.73
More than 500 workers	0.01%	0.19%	1222.47	3503.23	28.27	37.45

Notes: This table shows statistics on the firm size distribution in the model and in the data. The first two Columns list the share of firms in each quota group; the next two Columns report the average number of workers; and the final two Columns contain the average number of disabled workers.