The Labor Market Effects of Disability Hiring Quotas*

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Abstract

Affirmative action policies mandating firms to increase employment of minorities in the workplace have been implemented across the world. This paper studies the implications of enforcing modest hiring quotas for firms and workers using people with disabilities as the minority group. Using the introduction of a reform in Brazil that enhanced enforcement of a new hiring quota regulation, my market-level analysis indicates that people with disabilities in local labor markets more exposed to the reform experience larger increases in formal sector employment and earnings. To better understand the margins along which firms respond to the quota scheme, I leverage variation in enforcement across firms. This analysis reveals three key adjustment margins. First, the employment effects are concentrated among low-paying, less skilled jobs. Second, consistent with statistical discrimination, workers with disabilities hired prior to the quota experience reduced wage growth and promotion rates. Third, the quota does not come at a cost to other workers in terms of wages or employment, or to firms in terms of closure. Through the lens of a model of enforcement of hiring quotas with imperfect compliance, I show that the policy generates aggregate welfare gains. My findings illustrate that, in labor markets under imperfect competition, mandating modest increases in employment for the disadvantaged can promote redistribution and improve welfare.

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1 Introduction

More than one billion people, around 15 percent of the population, live with some form of disability worldwide, constituting one of the fastest-growing minorities (WHO (2011)). Yet, in most countries, their unemployment rates are among the highest, at least twice the rate of the general population (ILO (2007)). Because firms' willingness to hire people with disabilities, even those who can work, has been identified as a key limiting factor, policies to boost the demand for these workers are as crucial as social insurance programs.[1] Implemented in more than 100 countries (see Figure 1), affirmative action hiring quotas—whose origin dates back to the World War I when thousands of people were left disabled—are some of the most common policy levers available to reduce the unemployment rates and the fiscal burden of social insurance (ILO (2019)).

This paper assesses the implications of enforcing affirmative action hiring quotas for firms, workers, and government in the context of people with disabilities. Economists and policy makers have long debated about hiring quotas for disadvantaged groups. In competitive labor markets, the conventional wisdom is that quotas increase earnings at a potential cost of displacing the non-disadvantaged and reducing firm profits (Welch (1976), Leonard (1984), Griffin (1992), Coate and Loury (1993)). Under these assumptions, the gains for the disadvantaged may be offset by larger welfare losses to other agents. Recent literature, however, has documented extensive evidence of imperfect competition and frictions in the labor market (Card et al. (2013), Lamadon et al. (2022)). In such labor markets, firms may be inefficiently small in equilibrium, and hiring quotas may lead to efficient increases in employment and redistribute economic rents to the disadvantaged (Holzer and Neumark (2000)). This also holds true if discrimination is the source of employment gaps.

Despite the popularity of hiring quotas, there are two main reasons why examining their implications empirically has been difficult. One reason is the limited availability of linked data both containing information on firms who are (or not) under quota regulations and identifying individuals from targeted and non-targeted groups. Second, even when such data are available, the contentious nature of affirmative action and the lack of regulatory incentives in the private sector have made most hiring quota regulations toothless. This has also led governments to introduce reforms for stricter enforcement (ILO (2019)).

This paper overcomes these challenges by exploiting several features of the Brazilian setting. First, the country has a quota policy and an enforcement tool. The regulation establishes that firms with at least 100 employees must fill a minimum of 2 percent of their positions with people

[1] Non-discriminatory factors, such as work disincentives from social insurance, transportation barriers, lack of awareness of disability issues, and lower education levels, contribute to this scenario. Nonetheless, growing evidence from experimental and observational studies show that employers are less likely to hire people with disabilities (Baldwin and Johnson (1994), Ameri et al. (2018)).

with disabilities or individuals enrolled in vocational rehabilitation programs. Inspections are the main enforcement tool. Once inspected and found to be delinquent, firms have a grace period to meet the mandated share, or face a heavy fine. Features of the regulation and enforcement structures, along with the high frequency of inspections, create useful quasi-experimental variations for identification. Second, the availability of uniquely-detailed data at the individual- and firm-levels with rich information on people with disabilities, including the type of disability, education, hours of work, and occupation, provides a rare opportunity to identify heterogeneous effects across and within groups of workers and to overcome the perennial dearth of data that have long challenged the literature. Third, the large size of the country and its high disability prevalence bring extra statistical advantages when workers with disabilities are vastly underrepresented in the labor market. Fourth, the limited coverage of social insurance for people with disabilities implies that access to disability insurance programs, one often-hypothesized cause of low employment rates, is an unlikely key driver of disability inequality.

In the first part of this paper, I quantify the aggregate impacts of enforcing hiring quotas across local labor markets. I use Census data covering the entire population and exploit the introduction of a new reform in 2000, which established both the quota regulation and inspections as the main tool to enforce compliance. Along with the timing variation from the reform, I use geographic variation in the intensity of potential demand for workers with disabilities and enforcement of labor regulations. I exploit the interaction between pre-reform firm size distribution and enforcement capacity as the source of cross-sectional variation in exposure to the reform. Pre-reform size distribution predicts differential potential demand for people with disabilities induced by the regulation. Enforcement capacity is proxied by the distance to the nearest labor office (Almeida and Carneiro (2012)).

Consistent with the goal of expanding job opportunities, the market-level results indicate that people with disabilities in labor markets more exposed to the reform experience larger gains in employment and earnings. I document that the people with disabilities from more exposed local labor markets, like the cities of São Paulo or Rio de Janeiro, are 1.1 percentage points, or 10 percent, more likely to become employed in the formal sector ten years after the reform. Along with higher employment, their average earnings increase by around 9.5 percent. I find no evidence that people without disabilities and workers from the informal sector are affected. The aggregate results, albeit informative, are limited in showing how firms adjust to the mandated employment. Understanding the reallocation of firm activities in the cross section of firms is key to quantifying the policy incidence in light of extensive evidence of frictions in the labor market.

The second part of my paper closely examines adjustments within firms. My context permits an event study difference-in-differences design because, once inspected, firms may be required to meet the minimum quota. I compare how the outcome variables evolve for inspected firms with pre-inspection employment either above or below the hiring cutoff of 100 workers around the time of inspection. The estimation sample consists of the universe of all firms that were inspected and assessed for compliance with labor regulations, including but not limited to quota regulation, mitigating concerns related to selection into inspections. The key variation is that only firms with at least 100 employees are under the affirmative action quota. I show that firms both above and below the mandatory cutoff exhibit similar levels and trends in outcomes prior to the inspection.

Using the universe of inspected firms linked to the matched employer-employee data, I document an increase in employment among people with disabilities following inspections. On the extensive margin, firms under the quota requirement, on average, are 7.8 percentage points more likely to hire an employee with disabilities. On the intensive margin, these firms experience a 41.7 percent increase in the total number of employees with disabilities. The vast majority of the new hires are concentrated in low-paying occupations and have milder disabilities. They also predominantly come from unemployment, instead of being poached from other firms or disability reclassification, indicating potential fiscal savings. At the same time, there is no impact on employment of people without disabilities. I also do not find that firms are more likely to exit the formal sector or experience a decrease in average wages, both imperfect proxies for profits.

Turning to workers' outcomes, I show that workers with disabilities, rather than those without disabilities, are affected. Surprisingly, I find evidence of reduced wage growth of around 6 percent for disabled workers, driven by incumbent workers, at the firms under affirmative action quotas. I find no discernible impact on wage growth for workers without disabilities or new hires. I find little support that workers without disabilities with similar characteristics as workers with disabilities experience wage growth slowdowns. My results are robust to reweighting techniques accounting for dissimilarities in observable characteristics across disability status. I also document that workers with disabilities experience a decline in promotion rates. My empirical findings point to relevant distributional consequences: although the policy results in an increased representation of workers from the target group, it may also exacerbate workplace inequality in pay between groups.

What can explain the lower wage growth for incumbents with disabilities? I shed light on mechanisms by complementing the administrative data with an original survey conducted with human resources executives and personnel. Several pieces of evidence are consistent with a dynamic statistical discrimination model, in which firms are less able to interpret signals from a minority group. In line with reduced hiring standards, affirmative action hiring quotas reduce the average skill of the disabled group. I show that workers with less opportunities to send stronger signals drive the wage growth slowdowns. The data also reject irreversible fixed costs, compensating differentials, and retaliation due to whistleblowing as alternative explanations.

In the third part of the paper, I evaluate the implications of my findings for aggregate welfare. I develop a simple model of an enforcement of marginal hiring quotas under imperfect compliance. My model characterizes the changes in profits, surplus of workers with disabilities, and fiscal revenue following an inspection. The effect on profits depends on the wedge between marginal revenue products of labor and wages. Using a discrete choice framework on the decision to comply with the hiring quota following an inspection, I show that the data reject marginal product of new hires with disabilities lower than their wages. I also document that increased employment results in gains in surplus of workers with disabilities and fiscal revenue, suggesting aggregate welfare gains. Conceptually, these results are consistent with a labor market under imperfect competition characterized by discrimination at the hiring level. In such a labor market, a modest rise in mandated employment can achieve redistribution without harming overall efficiency.

This paper contributes to several lines of research. It speaks to a large literature, theoretical and empirical, studying the consequences of affirmative action quota regulations in labor markets on human capital investment and firm output (Welch (1976), Lundberg (1991), Coate and Loury (1993), Fang and Moro (2011)). Previous studies have focused on the redistribution effects, indicating positive or neutral impacts on the employment of minorities groups (Lalive et al. (2013), Peck (2017), Miller (2017), Prakash (2020)). Other empirical works analyze whether AA policies in educational settings impact economic efficiency through changes in final output, such as educational attainment and income (Bagde et al. (2016), Bleemer (2022), Schaede and Mankki (2022)).[2] My contribution is threefold. First, I contribute to this literature by leveraging unusually rich administrative data and new quasi-experimental research designs to provide novel evidence of the market-level impacts across local labor markets. Second, relative to past literature, I provide richer estimates of the causal impact of hiring quotas on workers' outcomes, including wages, turnover, part-time employment, and promotion. By providing evidence of heterogeneous impacts across worker groups, this work also adds new evidence on the distributional debate about the incidence of this policy. Third, I provide a comprehensive assessment of the implications for firms, workers, and government, which allows me to speak to the consequences for redistribution and efficiency.

This work also relates to a literature on the consequences of policies targeting people with disabilities. The core of this literature has focused on the supply side, such as the impacts of social insurance (e.g., disability insurance) and anti-discrimination regulations (e.g., Americans with Disabilities Act) on labor supply and consumption (DeLeire (1997), Acemoglu and Angrist

[2] In the context of leadership positions, a handful of papers have found that mandated representation of women on boards is associated with negative to neutral impacts on firm performance (Ahern and Dittmar (2012), Matsa and Miller (2013), Bertrand et al. (2019), Ferrari et al. (2021), Eckbo et al. (2022)).

(2001), Autor and Duggan (2003), Maestas et al. (2013), Kostøl and Mogstad (2014), Deshpande (2016), Autor et al. (2019), Aizawa et al. (2020)).[3] This paper differs from the prior literature in its focus on the demand side, since firms are also essential for the design of social insurance and welfare programs (Lalive et al. (2013), Mori and Sakamoto (2018), Aizawa et al. (2020)). I provide novel evidence of the interaction of enforcement and hiring quotas as fundamental policy levers to boost the demand for workers with disabilities.

At a broader level, this paper builds on a large literature assessing the incidence of regulations. In perfectly competitive labor markets, redistributive regulations cannot be justified on efficiency grounds. In view of a growing number of papers that have documented the existence of employer discrimination (Glover et al. (2017), Benson et al. (2022)) and imperfectly competitive labor markets, in which firms have some power to determine wages and set inefficiently low employment levels (Card et al. (2013), Lamadon et al. (2022)), recent evidence suggests that regulations have the potential to improve efficiency and achieve redistribution (Manning (2011)). Examples of price regulations in labor markets examined in the literature include payroll taxes (Saez et al. (2019)), minimum wage (Harasztosi and Lindner (2019)), wage floor (Card and Cardoso (2021)), and hiring credits (Cahuc et al. (2019)). Wage subsidies are perhaps the most prominent example of regulations with the goal of creating job opportunities for the disadvantaged. Most of the evidence, however, indicates that wage subsidies do not increase employment for disadvantaged groups (Katz (1996), Bartik (2001), Huttunen et al. (2013)).[4] This paper focuses on a particular form of quantity regulation that mandates employment for the disadvantaged. My findings indicate that, in labor markets with frictions, enforcing modest quotas can be an efficient pathway for countering the low employment of people with disabilities.

The remainder of this paper is structured as follows. Sections 2 and 3 describe the institutional context and data. Section 4 presents the aggregate impacts of enforcing the quota policy. Section 5 analyzes how firms make adjustments and potential mechanisms underlying the earnings effects. In Section 6, I discuss implications for welfare. Section 7 concludes.

[3] A common policy among OECD countries is anti-discrimination legislation. The Americans with Disabilities Act, enacted in 1991 in the US, is the most prominent example of an anti-discrimination law aiming to provide better jobs opportunities, prohibit firms from discriminating based on disability, and mandate reasonable accommodations to workers. Several works indicate that the introduction of the ADA increased the costs of hiring workers with disabilities, creating incentives for firms to avoid hiring them (DeLeire (1997), Acemoglu and Angrist (2001)). There is a large literature showing that anti-discrimination legislation does not increase employment in other contexts (Bell and Heitmueller (2009), Lalive et al. (2013)).

[4] Despite the limited evidence of effectiveness of wage subsidies for the disadvantaged, a handful of papers have shown that wage subsidies can stabilize labor demand in recessions (Neumark and Grijalva (2017), Schoefer (2021)).

2 Institutional Context

2.1 Disability Gaps in the Labor Market

In most countries, the employment gap between people with and without disabilities is substantial, leading to high welfare dependency and poverty rates. The unemployment rates among working-age people with disabilities are at least twice the general level (ILO (2007)). Non-discriminatory factors, such as work disincentives from social insurance, transportation barriers, lack of awareness of disability issues, and lower education levels, contribute to this scenario. Employers' willingness to take on workers with disabilities still constitutes a major challenge. Randomized audit studies point to lower employer callback rates for applicants with disabilities (Ameri et al. (2018)). Observational studies show that firms are less likely to hire people with disabilities (Baldwin and Johnson (1994)). Workplace accommodation and productivity concerns do not entirely explain the employment gaps.

Like many countries, such as Germany, Hungary, Poland, Sweden, and Turkey, Brazil adopts a medical approach to disability. Disability is defined as an impairment of a physical, mental, intellectual or sensory nature, which, in interaction with other barriers, may hinder the full and effective participation of people with disabilities in society on equal terms relative to others. According to the 2010 Census, 22.4 percent of working-age Brazilian aged between 25 and 54 report living with some form of disability, while 6.7 percent disclose having a severe disability.[5] Even with the challenges associated with defining disability and the lack of standardized disability statistics on a global scale, these numbers are comparable to other countries, such as New Zealand, the US, and the UK.

Despite their high prevalence, people with disabilities are still vastly underrepresented in the labor market. Records from the 2010 Census data reveal striking disability gaps among the working-age population. Table A1, Appendix A, shows that nearly 79.4 percent of non-disabled aged between 25 and 54 are economically active. On the other hand, people with some (severe) disabilities are 2.6 (18.2) percentage points less likely to be economically active. Having some (severe) disability is also associated with lower employment rates by 2.2 (5.7) percentage points among economically active individuals. Conditional on working, people with disabilities earn about 9.9–19.5 percent less than those without disabilities. These remarkable gaps, which are not explained by differences in location, educational level, potential experience, occupation, or economic sector, illustrate substantial labor market differences even for people with disabilities who can work.

An unconditional cash transfer (*Benefício de Prestação Continuada*) equivalent to a monthly minimum wage (about USD 235) is available to very poor people who have severe disabilities and

[5] The Census asks whether the respondent lives with severe, some or no difficulties in each of the following activities: seeing, hearing, and walking and climbing stairs. In addition, the Census also collects information on whether the individual has a permanent intellectual disability.

do not meet household per capita income above one quarter of the minimum wage. The transfer does not require previous contributions to social security. The coverage is quite limited: only the very poor with severe disabilities that hinder independent living and work capacity are eligible for the transfer. In 2010, less than 4 percent of people with disabilities received this transfer, suggesting that work is their main source of income.

2.2 2000 Reform

Heeding global efforts to reduce disability inequality, the federal government enacted the Anti-Discrimination Act (National Policy for People with Disabilities or Decree 3,298), which came into effect in 2000 (henceforth 2000 reform). Relevant to the paper, the Act consisted of three main features. First, it provided a legal definition for the term "disability" and a preliminary list of medical conditions required to qualify for disabled status. Examples of disabilities include mobility and physical impairments (e.g., paraplegia, monoplegia, amputation or absence of limb, limbs with congenital or acquired deformity, among others), moderate to profound hearing loss, moderate visual impairment to blindness, and selected mental disorders. Appendix A contains a full list of disabilities recognized by the Act.

Second, the Act regulated the affirmative action quota (henceforth AA quota) by mandating firms in the private sector with at least 100 employees to fill a minimum of 2 percent of positions with people with disabilities or individuals enrolled in a vocational rehabilitation program from the Social Security. The reserved share increases in firm size: firms with 201 to 500 (501 to 1,000) employees must meet a quota of 3 percent (4 percent), while those with more than 1,000 employees have a quota of 5 percent.[6]

The third key element is the utilization of labor inspections as the main enforcement tool to promote compliance with the AA quota. Due to regulatory intricacies, oversight and monitoring of the AA quota through labor inspections became possible after 2003, when the Ministry of Labor started to collect information on workers with disabilities in the formal sector and established administrative fines and penalties for delinquency.[7] In short, the 2000 reform—which created instruments to define disabilities, mandate reserved jobs through the AA quota regulation, and boost its compliance—represented the first legal framework aimed at increasing employment for people with disabilities.

[6]The AA quota regulation was first launched in 1991 with the Law 8,213. However, the federal government only formally regulated the AA quota and its functioning after the Anti-Discrimination Act.

[7]The first rules establishing the formal inspection procedures for the AA quota regulation (Normative Instruction SIT 20) and the administrative fines and penalties for non-compliance (Normative Instruction SIT 36) arose in 2001 and 2003, respectively.

2.3 Enforcement of Affirmative Action Quota

Brazil has a rigid legal structure with numerous mandated benefits to workers (e.g., minimum wage, unemployment insurance, and severance pay), high dismissal costs, and burdensome tax requirements. Imperfect compliance with labor regulations is quite common. In many cases, firms choose to hire workers without fully complying with several regulations—such as payments to social security and hiring people with disabilities—or even choose to hire informal workers.

The Ministry of Labor is responsible for verifying compliance with labor regulations and uses labor inspections as the main enforcement tool. The enforcement capacity has a decentralized structure: each state has its own state labor office (*delegacia*) located in the state capital, and each state may also have additional local labor offices (*subdelegacias*) in other municipalities, depending on the state's size and economic importance.[8] Inspections can be triggered by random firm audits or anonymous reports from numerous sources, such as workers, labor unions, or the prosecutor's office. In practice, most inspections are triggered by anonymous reports since most labor offices are understaffed (Almeida and Carneiro (2012)).

The technology of enforcement is straightforward. Inspectors are assigned to a specific local labor office and must travel by car to inspect firms. This generates substantial spatial variation, since smaller distances to labor office imply a higher probability of inspection and, as a result, enforcement capacity (Ponczek and Ulyssea (2021)). Once inspected, firms may be assessed for compliance with labor regulations. The key feature, fundamental to my research design, is that *only* firms with at least 100 full-time employees may be required to fill 2 percent of positions with workers with disabilities.

Firms that fail to meet the AA quota may be notified and granted a grace period to comply with the regulation. In case of continued non-compliance, a heavy fine, which typically ranges from 2.5 to 250 monthly minimum wages per missing worker, may be imposed unless the firm shows concrete evidence of effort and failure in hiring workers with disabilities.[9] To qualify for the job reserved to the AA quota, the worker needs to present a medical report containing the type of disability and its code following the International Classification of Diseases (ICD). To minimize moral hazard or

[8] Brazil has 27 states, implying that there are 27 state labor offices (*delegacia*). States with low population density, like Acre, Amapá, and Tocantins, have only one labor office (*delegacias*). More dynamic states, like São Paulo and Minas Gerais, have at least 20 local labor offices (*subdelegacias*) besides their own state labor office (*delegacia*).

[9] The final amount of fines is a function of the number of workers with disabilities or rehabilitated workers that firms fail to hire in compliance with the AA quota regulation. It may also depend on numerous factors, such as firm size, recidivism, economic sector, and geographic location. In some cases, firms may be exempted from the hiring quota if they present proofs of attempts to comply with AA quota regulation (e.g., frequent job postings targeting people with disabilities, lack of qualified candidates, etc.). In these cases, the firms may be granted an extended grace period and asked to sign a statement confirming commitment to comply with the AA quota regulation. In addition, several firms (e.g., firms from civil construction and oil and gas industries) can obtain exemption from AA quota via lawsuits alleging that it not possible to guarantee safe work conditions to employees with disabilities.

frauds in the hiring process, the worker must provide consent in disclosing this information. The penalties for providing fraudulent information can be quite severe.[10]

3 Data

This paper uses three primary data sources: data on labor inspections provided by the Ministry of Labor, the matched employer-employee records covering the entire formal sector, and the decennial Demographic Census data covering the Brazilian population.

Labor Inspections. The first source of data consists of reports summarizing labor inspections conducted by the Ministry of Labor. The data contain detailed information on tax identifiers, the dates on which the reports are submitted (used as the start dates of inspections), and the labor violations (e.g., formal registration, hours of work, severance pay, minimum wage, etc.) found during inspections.

Firm- and Woker-Level Data. Labor market information are extracted from RAIS (*Relação Anual de Informações Sociais*), a matched employee-employer data from the Ministry of Labor. It provides a comprehensive and high-quality annual overview of the formal sector (Szerman (Forthcoming)). Firms report information on their workers, including hiring and separation dates, average annual wages, number of hours contracted, occupation, and demographic characteristics, including gender, age, educational level, race and disability status and type of disability. Because information on whether the worker has a disability and the type of disability only started to be reported in 2003, I link firms who have been inspected to the RAIS datasets from 2003 and 2014, the last year before a deep economic recession hit the country.[11]

Census Data. The third dataset consists of the decennial Brazilian Demographic Census from 2000 and 2010 sourced from IBGE (Brazilian Institute of Geography and Statistics). The Census contains information on individuals' demographic and socioeconomic characteristics and labor market outcomes, including self-reported degree and type of disability, employment status, and work

[10]Informal conversations with inspectors indicate that frauds do not represent a major concern in the Brazilian context because potential financial penalties and reputational damages for fraudulent practices are much more severe than the penalties for non-compliance.

[11]Disability status and type of disability are rarely reported in the matched employee-employer data from other countries, limiting progress in research on the role of employers and workplace policies on disability disadvantage in labor markets. This limitation has been described in Baldwin and Johnson (2006): "*there is also a serious shortage of data that support empirical analyses of the labor market experiences of persons with disabilities. (...) The ideal data set includes detailed information on employment, wages, work experience and job characteristics, as well as information on health conditions, functional limitations and disability status.*"

and non-work (e.g., welfare benefits) incomes. These two waves of Census data allow me to obtain variables of interest before and after the reform. Relative to the matched employee-employer data, the Census has the advantage of providing labor market outcomes outside the formal sector. Due to fundamental methodological differences in questions regarding disabilities from the 1991 and 2000 Censuses, I do not use the Census data from 1991, the first edition with questions on disability.[12]

Other Data. I rely on additional minor sources of data to conduct the main analyses. I gather labor offices' addresses from official sources and link them to their date of creation extracted from Ponczek and Ulyssea (2021) to maintain labor offices created prior to the enactment of the regulation. I also utilize these information to construct a measure of enforcement capacity by computing the minimum distance between each micro region and the nearest labor office using the Google Maps API.[13] To disentangle several mechanisms behind the results, I also make use of an original pilot survey conducted with human resources executives and personnel.

4 Aggregate Analysis

The context suggests that labor markets with a high concentration of large plants and frequent labor inspections are more likely to experience an increase in the demand for workers with disabilities after the 2000 reform. To gauge the aggregate effects of the reform on employment and earnings for people with and without disabilities across local labor markets, this section proposes an identification strategy that exploits two dimensions of the reform: the timing of its enactment and the spatial heterogeneity in potential exposure.

4.1 Exposure to the 2000 Reform

I construct a measure of local exposure to the reform in three steps. First, I define local labor markets at the micro region level. In Brazil, micro regions consist of an aggregation of economically integrated contiguous municipalities with similar economic and geographic characteristics. These micro regions delineate local economies, similarly to commuting zones in the US. Second, I define

[12]The 1991 Census data has a single question asking respondents if they have one or more of the following conditions: blindness, deafness, hemiplegia, hemiplegia, paraplegia, and intellectual disability. Only 1.23 percent of the working-age population reported having disabilities as opposed to 6.7 (22.4) percent with severe (some) disabilities in 2010. The 2000 and 2010 Censuses ask respondents whether they live with severe, some or no difficulties in seeing, hearing, and walking and climbing stairs separately, and whether they have a permanent intellectual disability. Throughout this paper, I define individuals who report living with some or severe difficulties as persons with disabilities.

[13]I obtain the distance between the centroid of each municipality and the nearest labor office created prior to 2000s. I then define the minimum distance of the municipalities that belong to each micro region as the minimum distance between each micro region and the nearest labor office, which is used as a proxy for enforcement capacity.

potential demand for workers with disabilities across local labor markets as the share of people with disabilities that would potentially benefit from jobs reserved by the AA quota regulation:

$$\textit{potential demand}_r^{pre} = \frac{\textit{potential jobs}_r^{pre}}{\textit{total PwD}_r^{pre}}. \tag{1}$$

The numerator, $\textit{potential jobs}_r^{pre}$, represents the total number of jobs in the private sector available to people with disabilities in each micro region r if there is perfect compliance with the AA quota. I calculate this number from the distribution of firm size in 1998, prior to reform, extracted from RAIS data.[14] The denominator, $\textit{total PwD}_r^{pre}$, normalizes potential jobs by the pre-reform number of people with disabilities in each micro region r, calculated from the 2000 Census. The term $\textit{potential demand}_r^{pre}$ ultimately captures pre-reform spatial heterogeneity in potential demand for workers with disabilities across local labor markets and has a median ratio of 5 percent. I then classify micro regions above and below this median as micro regions with strong and weak potential demand. Figure B1, Appendix B, shows how potential demand varies geographically. The areas with strong potential demand are concentrated in the Southeast and South regions, which are the most developed regions in the country with larger labor markets.

The third step consists of building off a measure of enforcement capacity developed by Almeida and Carneiro (2012) and used in other papers (Haanwinckel and Soares (2021), Ponczek and Ulyssea (2021)) to exploit spatial heterogeneity in enforcement of labor regulation. The Ministry of Labor adopts a straightforward technology of enforcement, requiring only two inputs: inspectors who are assigned to labor offices and travel distance by car between labor offices and inspected firms. In principle, micro regions located farther away from labor offices are less likely to receive inspections. Figure B4, Appendix B, confirms this negative relationship between the number of inspections per firm and the distance to the nearest labor office. It motivates the use of minimum travel distance to the nearest labor office within each micro region as a proxy for enforcement capacity.[15] To ensure that the measure of enforcement capacity does not respond to changes in local labor market conditions and adjustments to the hiring quota regulation, I restrict the analysis to labor offices created before the reform. The median distance is about 60 kilometers (or 66 minutes). I then classify micro regions with pre-determined distances below and above the median as those with weak and strong enforcement capacity. Figure B2, Appendix B, illustrates the variation in enforcement level across micro regions.

[14] This number is calculated from the RAIS data, which contain information on the total number of employees in each firm and the micro-region where the firm is located.

[15] For each municipality, I calculate the driving distance from its centroid to the nearest labor office that belongs to the same state. The set of labor offices is restricted to those created prior to 2000. I then take the minimum of the distances from all municipalities belonging to each micro region r to define the measure of enforcement capacity at the micro region level. The results are robust to alternative definitions, such as maximum and average distances.

To retrieve a cross-sectional variation, I interact the potential demand and enforcement capacity measures to compute the initial levels of local exposure to the reform. Figure 2 plots the geographic variation of the four classifications of the interaction term. Intuitively, persons with disabilities from areas with strong potential demand and enforcement levels should experience larger labor market responses relative to those located in areas with weak potential demand or/and weak enforcement capacity. Important to the empirical strategy, this cross-sectional variation is pre-determined with respect to the introduction of reform.

4.2 Empirical Strategy

My empirical strategy for the market-level analysis considers both the timing of the reform and the spatial heterogeneity in exposure to it. Put differently, I estimate the following regression model using the Census data:[16]

$$\begin{aligned} y_{rst} = \alpha + (\mathbf{1}_r^{SD,SE} \times Reform_t)\beta_1 + (\mathbf{1}_r^{SD,WE} \times Reform_t)\beta_2 + (\mathbf{1}_r^{WD,SE} \times Reform_t)\beta_3 + \\ \alpha_r + \alpha_t + \alpha_s \times t + X_{r,2000}\lambda + \varepsilon_{rst}, \end{aligned} \tag{2}$$

in which subscripts r, s, and t stand for micro region, state, and time; the indicator variables $\mathbf{1}_r^{SD,SE}$, $\mathbf{1}_r^{SD,WE}$, and $\mathbf{1}_r^{WD,SE}$ represent micro regions with strong potential demand and enforcement capacity, with strong potential demand and weak enforcement capacity, and with weak potential demand and strong enforcement capacity, respectively; $Reform_t$ is an indicator for the period after the 2000 reform; α_r and α_t delineate micro-region and time fixed effects; $\alpha_s \times t$ represents state-specific trends; $X_{r,2000}$ is the vector of baseline characteristics of the micro regions in 2000, including the share of female population, share of population with college education, share of urban population, unemployment rate, income per capita, and total population, all interacted with time fixed effects; y_{rst} is the labor market outcome of interest. Standard errors are clustered at the state level.

The coefficients of interest—β_1 to β_3—capture differential labor market responses across micro regions with distinct levels of exposure relative to micro regions with weak potential demand and enforcement capacity before and after the reform. To assuage concerns related to common shocks affecting micro regions and time-invariant characteristics of micro regions that might be correlated with both the exposure measure and the outcomes of interest, this specification includes both time and micro region fixed effects. I also add state-specific trends to control for policies or unobservable

[16] The aggregate analysis uses the Census data to provide an overview outside the formal sector. In addition, information on disabilities from the RAIS data started to be collected in 2003, after the reform. In Section 4.3, I propose an exercise using RAIS data and find similar patterns.

shocks specific to states. The set of baseline controls X_{rt} accounts for heterogeneous initial characteristics that can also influence the labor market outcomes, permitting differential trends across micro regions with heterogeneous initial characteristics.[17]

This empirical strategy relies on the assumption that, conditional on the set of baseline characteristics, the cross-sectional local exposure measure is orthogonal to omitted characteristics correlated with differential changes in labor market outcomes for people with disabilities after the reform. While it is not possible to directly test for this assumption, three additional pieces of evidence mitigate concerns related to the empirical strategy. First, the cross-sectional variation is constructed to be pre-determined with respect to the reform's passing. Second, I find no evidence of pre-trends when using alternative data (see Section 4.3). Third, I also examine the effects on the informal sector and people without disabilities as placebo tests. One could argue that some omitted characteristics, captured by the exposure measure, may remain unaccounted for. In this context, it is hard to think of omitted variables that would simultaneously lead to an increase in formal employment and no impacts on informality for people with disabilities in response to the reform within the same state and after controlling for the set of baseline controls. In addition, I do not find evidence that workers without disabilities from both the formal and informal sectors are affected by the reform.

Sample and Summary Statistics. Starting with individual-level data from the Census, the sample includes working-age population aged between 25 and 54 from to focus on individuals with strong labor force attachment. For each micro region, I separately compute employment and informality rates and average incomes for people with and without disabilities . Table C1, Appendix C, displays the summary statistics of the variables used in the aggregate analysis and confirms that people with disabilities have worse labor market prospects than those without disabilities. Most variables display a high dispersion, indicating that micro regions are quite heterogeneous.

4.3 Market-Level Results

I begin by documenting the relationship between local exposure measures and changes in employment. Table 1 compares micro regions that belong to each of the three groups of exposure to those with weak potential demand and enforcement capacity. Column (1) indicates that the reform leads to a significant increase by 1.1 percentage points (p.p.) in the share of people with disabilities

[17]Although the exposure measure is constructed to be pre-determined with respect to the introduction of the quota regulation, it might be correlated with initial labor market characteristics for people with disabilities across Brazilian micro regions. For instance, micro regions with different initial levels of economic characteristics might undergo different labor market paths, implying that our estimates could capture differential economic trends across micro regions. Including baseline observable characteristics of micro regions in 2000, interacted with time fixed effects, allows for differential trends across micro regions with heterogeneous initial characteristics.

who are employed in the formal sector exclusively in local labor markets with strong potential demand and enforcement capacity. The magnitude is equivalent to an increase by 9.5 percent relative to the baseline mean of 0.116 in 2000. In other words, moving a region from the lower to the upper median of the distribution of enforcement capacity and potential demand would induce an increase of 9.5 percent of formal employment for people with disabilities.

Column (1) confirms that labor market prospects for workers with disabilities located in areas with either weak potential demand or weak enforcement capacity remain unaffected after the reform, reinforcing the strong complementarities between enforcement and regulation. As falsification tests, Columns (2) to (4) assess whether the exposure measure is correlated with changes in formal employment for people without disabilities or in the informal sector. I find small and statistically insignificant coefficients across all specifications. The lack of changes in informality rates for people with disabilities also suggests that the increase in formal employment comes from non-employment.

Turning to the effects on earnings, Table 2 shows that only micro regions with strong potential demand and enforcement capacity display larger impacts on income from work for people with disabilities. The average work income rises by around 34.55 Brazilian *reais*, equivalent to a 9.5 percent increase relative to the baseline mean in 2000. It is a mechanical result as the reform is also associated with higher employment levels for this group. I do not find evidence of spillovers on non-work income (Column (2)) or people without disabilities (Columns (3) and (4)). These findings reveal that the benefits of the reform are mostly accrued by people with disabilities from local labor markets with higher exposure to enforcement capacity and AA quotas.[18]

Robustness Checks. I conduct some additional checks to probe the robustness of the aggregate analysis. First, Table C3, Appendix C, shows that the main conclusions do not change when considering the mean and maximum travel distances as alternatives to the minimum distance to calculate the exposure measure of enforcement capacity. Second, I use RAIS data to overcome the lack of pre-reform years in the Census. Because information on disability only started to be collected in 2003, I utilize data from 2003 to 2018 to identify individuals ever reported as disabled to assign retroactive information on disability to individuals found in RAIS between 1997 and 2002. This approach, albeit imperfect, permits an indirect test for pre-trends using the share of people with disabilities in the formal sector as the outcome variable. Figure B5, Appendix B, corroborates the

[18]Table C2, Appendix C, considers work income from the formal sector and work income from the informal sector as outcome variables. These definitions are different from overall work income in Table 2. Conditional on employment, I do not find differences in work income in both the formal and informal sectors, corroborating that the baseline gains in earnings are driven by higher employment in the formal sector rather than higher earnings among the employed. Manning (2011) argues that increasing mandated employment does not necessarily translate into an increase in wages. Firms can increase recruitment activity to generate extra supply or reduce worker quality. I document evidence of both strategies in Section 5.

lack of pre-trends and validates the previous findings. Third, Column 1 of Table C4, Appendix C, confirms that migration does not drive the increase in employment, mitigating concerns that the reform induced spatial reallocation of people with disabilities to more exposed local labor markets.

5 Firm-Level Analysis

The market-level results reveal that the reform induced higher formal employment and earnings for people with disabilities in more exposed local labor markets without generating spillover effects to workers without disabilities or workers in the informal sector. An interesting question is whether and how firms adjust to the mandated employment. Understanding the reallocation of firm activities in the cross section of firms is key to quantifying the policy incidence in light of extensive evidence on the role of firms in shaping labor market inequalities. To address this question, I combine the requirement for firms with at least 100 employees to have workers with disabilities and the variation in the exposure to the affirmative action quota generated by inspections. The firm-level analysis provides compelling graphical evidence in the short- and medium-terms and examines a broad range of outcomes and mechanisms.

5.1 The Employment Effects

5.1.1 Empirical Strategy

In the first part of the firm-level analysis, I estimate the employment effects of the hiring quota. Because the AA quota is rarely enforced without labor inspections and only firms with at least 100 employees may be required to hire workers with disabilities, my empirical strategy exploits both the AA quota requirement and the precise timing of the labor inspections by comparing inspected firms with pre-inspection employment levels above and below the cutoff of 100 workers, which represent treatment and control firms, before and after inspection. I estimate the following event-study model:[19]

$$y_{jt} = \sum_{k=-6}^{k=12} [\beta_k^{Quota} \times \mathbf{1}(t_j = t^* + k) \times Quota_{j,-1} + \theta_k \times \mathbf{1}(t_j = t^* + k)] + \alpha_j + \alpha_t + X_{jt}\gamma + \varepsilon_{jt}, \quad (4)$$

[19] In addition to the event-study analysis, I also perform difference-in-differences analyses in which I pool pre- and post-inspection quarters and estimate the average employment changes considering the following model:

$$y_{jt} = \alpha_j + \alpha_t + \tilde{\beta} \times Post_t \times Quota_{j,-1} + X_{jt}\gamma + \varepsilon_{jt}, \quad (3)$$

in which subscripts and the set of controls and fixed effects are the same as in Equation (4), and $Post_t \times Quota_{j,-1}$ is an indicator variable equal to 1 for all quarters after inspection in firms under the AA quota. As before, standard errors are clustered at the firm level.

in which subscripts j and t stand for firm and quarter-year; $\mathbf{1}(t_j = t^* + k)$ are dummies indicating an event in quarter-year k relative to the quarter-year t^* in which the firm is inspected; $Quota_{j,-1} = \mathbf{1}(\text{Emp}_j \geq 100)$ is an indicator variable for firms with at least 100 employees in the quarter-year prior to inspection, which represent the treated group; α_j are firm fixed effects; α_t are quarter-year fixed effects; X_{jt} are time-varying firm-level controls and include state- and industry-specific trends; and y_{jt} is the employment outcome of interest. Year fixed effects control for common shocks affecting the firms each quarter-year. Firm fixed effects control for time-invariant characteristics of firms that might be correlated with the outcomes of interest and the AA quota requirement. Standard errors are clustered at the firm level.[20]

The post-event coefficients of interest—β_k^{Quota}—capture the dynamics effects of the AA quota requirement relative to the quarter-year before the labor inspection. To mitigate concerns related to selection into labor inspections, the sample contains *all* firms who have been inspected. Once inspected, the firms are assessed for compliance with the main dimensions of the labor regulation, including formal registration, minimum wage, and mandated benefits. The key difference is that *only* firms with at least 100 employees by the time of the inspection may be assessed for compliance with the AA quota targeting people with disabilities, allowing me to exploit the differential impacts based on the regulation threshold. To my knowledge, there is no other firm regulation using the threshold of 100 employees in the country. Identification in Equation (4) relies on the timing of labor inspection being uncorrelated with the outcomes of interest, *conditional* on firm and time fixed effects and firm-level controls, X_{jt}. The key identifying assumption is that outcomes for treated and control firms would have followed parallel trends in $k > 0$ if no inspection had occurred for treated firms. I test this assumption by assessing whether the pre-event coefficients of interest are statistically indistinguishable from zero.

The estimates are likely to be biased if firms in different size categories had different trends in the absence of labor inspections. For instance, economic shocks might have affected large and small firms differently. I implement several additional steps to assuage these concerns. First, the baseline specification includes a local sample of firms with pre-inspection employment levels between 75 and 125 employees. Second, I probe the robustness of my main results by considering narrower bandwidths around the cutoff of 100 employees and dropping firms very close to it. Third, time-

[20] One natural candidate for identification in this context is the use of a local regression discontinuity design (RDD). However, this strategy is not compelling because the running variable is rarely well-defined in the data for employment measures and there is some potential firm selection around the threshold of interest. Including firm and time fixed effects, along with industry and location trends, mitigates concerns related to firm selection and allows me to focus exclusively on the variation occurring across quarters and within firms. Another potential candidate is the bunching estimator. As shown in Figure D1, Appendix D, there is no visual evidence that firms bunch below the 100 employees threshold, suggesting that firms do not avoid being subject to the AA quota regulation. These pieces of evidence motivate dynamic difference-in-differences design as my main empirical strategy.

varying controls X_{jt} include state- and industry-specific trends to control for policies or unobservable shocks specific to states and industries.

To capture the employment effects of the AA quota, I consider four complementary outcomes: the extensive and intensive margins of employment responses, measured by an indicator variable for having at least one worker with disabilities and an inverse hyperbolic sine transformation of the number of workers with disabilities, the share of workers with disabilities, defined as total workers with disabilities divided by the total number of workers in each firm, and an inverse hyperbolic sine transformation of total workers without disabilities.[21] In Appendix D, I additionally examine the impacts on hires and separations of workers with and without disabilities.

Sample and Summary Statistics. I take several steps to construct the sample of interest. First, I obtain a list of firms who have been inspected together with the earliest date of inspection reports to avoid duplicated observations. I do not impose any restriction related to violations brought by inspections. After generating quarterly labor market information from the RAIS data, the second step consists of matching the list of inspected firms to the quarterly data.[22] Third, I limit the sample to firms found in the RAIS data from six quarters before to twelve quarters after the first inspection, allowing me to estimate the dynamic impacts spanning almost five years. Fourth, I categorize firms with less or more than 100 employees as control and treatment groups using information on the total number of employees in the quarter before the inspection since it is the criterion used by inspectors to assess compliance with the AA quota.

Table E1, Appendix E, presents summary statistics for both groups after aggregating data for the quarters before and after inspections. The numbers confirm that, prior to inspections, control and treatment firms are comparable along observable dimensions, such as the number of workers with disabilities, share of workers with disabilities, log average earnings, location, and sector distribution. The only exception is that, as expected, control firms have, on average, less employees (72.23 employees) relative to the treated firms (93.24). After inspections, employment measures for people with disabilities experience larger increases in treated firms. For instance, the average number of employees with disabilities increases from 0.48 to 0.74. In addition, 25 percent of treated firms report having at least one worker with disabilities after inspections, compared to 12 percent from the pre-inspection period. Control firms experience more modest increases along these

[21] I apply an inverse hyperbolic sine transformation to handle zeroes in the data. The transformation is given by $asinh(y) = \log(y + \sqrt{y^2+1})$. As robustness checks, I also show that my results are robust to adding one before taking the log, using the absolute number of workers with disabilities, and replacing the ordinary least square estimates with a conditional fixed-effect Poisson model.

[22] Since RAIS data do not contain quarterly information on employment, I combine worker-level information on hiring and separation to transform annual data into quarterly data.

dimensions, corroborating that compliance with quota is not required for them after inspections.

5.1.2 Firm-Level Results

This section presents my main results. I start by documenting the impacts of the AA quota on employment. I then investigate whether other firm outcomes, including average earnings and profits, proxied by firm exit, change. I also discuss other margins of firm responses by analyzing heterogeneity across occupations, educational level, and type of disabilities. I perform several tests to probe the robustness of my main results.

Effects on Employment. I document strong and persistent increases in employment for people with disabilities resulting from enforcement of the AA quota. Figure 3 displays $\hat{\beta}_k^{Quota}$, along with 95 percent confidence intervals, after estimating Equation (4) for selected variables. The pre-event coefficients are statistically equal to zero, supporting the assumption that both treatment and control firms have similar pre-inspection trends. Following inspections, there is a sharp increase in the number of workers with disabilities, a pattern that becomes strong and persistent over time.

Panel A of Table 3 reports the immediate ($k = 0$), short-run ($k = 6$), and long-run ($k = 12$) impacts, whereas Panel B displays the aggregate impacts. The point estimates for employment for persons with disabilities grow within three years (Column (1) and Figure 3(a)). The magnitude of the estimate indicates an increase of 41.7 percent in the number of workers with disabilities after inspections.[23] Considering the extensive margin of employment, Column (2) and Figure 3(b) report that treated firms, in the long run, are 7.7 p.p. more likely to have at least one employee with disabilities after inspections. Column (4) and Figure 3(d) show that this increase is not followed by a significant decline in log workers without disabilities. In addition, Appendix D presents the findings for new hires and separations, confirming that adjustments in employment mostly come from higher arrival rates rather than lower departure rates. This suggests that search frictions are unlikely to constitute a major barrier of compliance with the AA quota.

Effects on Other Firm Outcomes. I also investigate other margins of responses to understand whether firms finance new hires through lower average wages or profits. Because I do not have data on firm profits, I utilize an indicator of exiting the formal sector as an imperfect proxy for profits. Exit is defined as equal to one if the firm does not have any formal employee in a given quarter-year. Table 4 indicates no evidence of statistically significant impacts on wages for workers

[23] Bellemare and Wichman (2020) derive the elasticity for an arcsinh-linear specification, which is equivalent to $\hat{\beta}x\frac{\sqrt{y^2+1}}{y}$.

without disabilities, or for firm exit.[24] In addition, I find no evidence for avoidance in the form of bunching below the threshold that would arise in case of costly compliance with the regulation.

Heterogeneity. The richness of the RAIS data allows me to scrutinize the extent to which firms respond to the AA quota considering different levels of corporate hierarchy. I have information on occupations, allowing me to categorize each worker into one of the following categories: (i) managers (e.g., manager and director); (ii) high-skill professionals (e.g. researchers, teachers, doctors, nurse, engineers, technicians, architects, mathematicians, and statisticians); (iii) low-skill white collar jobs (e.g., cashier, receptionist, secretary, and library assistant); and (iv) blue collar jobs. Figure D3, Appendix D, shows that the increase in employment for people with disabilities is concentrated among low-skill, low-paying occupations.[25] Concerning heterogeneity across educational levels, Figure D3 confirms that firms recruit more from those without college degree.

Another important source of heterogeneity relates to the distinction between different types of disabilities, a unique feature from the Brazilian data. Starting in 2006, employers report whether the worker has one of the following disabilities: physical, hearing, visual, intellectual, or multiple (two or more disabilities). Individuals who received vocational rehabilitation services may also be classified as having disabilities for quota purposes. Figure D3 indicates that firms are more likely to hire workers with physical disabilities, followed by hearing and other disabilities, suggesting preferences for milder forms of disabilities.[26]

Robustness Checks. Table E5, Appendix E, reports additional checks to ensure that my findings are robust to alternative variable, specification, and sample definitions. Column (1) repeats the benchmark specification from Table 3. Columns (2) and (3) confirm that conclusions regarding employment of people with disabilities do not change when considering total number of employees

[24] Evidence on the impacts of the AA quota on profits is mixed. Consistent with my results, Mori and Sakamoto (2018) find that firm profits are not affected in Japan despite the increase in employment of people with disabilities. Peck (2017) documents opposite findings in Saudi Arabia's *Nitaqat* program, which determined quotas to hire Saudis at private firms. Unlike my context, the Saudi program required aggressive quotas for firms.

[25] Consistent with this result, in the US context, Holzer and Neumark (1999) show that firms under affirmative action are more likely to hire women and minorities with lower levels of education and for jobs with lower skill requirements. The authors do not find evidence of weaker performance of these new hires.

[26] Tables E2– E4, Appendix E, display the point estimates for the heterogeneity analysis. Because visual, intellectual, and multiple disabilities represent a small fraction of disabilities, I pool them together. Unfortunately, RAIS data does not contain further details on disabilities. Instead, I use an alternative source of data from the public sector with personnel records from the federal government in 2022 to get a sense of the distribution of disabilities between employed individuals: partial visual impairment (16.72 percent); congenital or acquired deformity (13.11 percent); reduced mobility, permanent or temporary (10.17 percent); partial hearing impairment (8.46 percent); bilateral hearing impairment (5.98 percent); monoparesis (5.33 percent); amputation (5 percent); deafness (4.73 percent); paraplegia (3.66 percent); monoplegia (3.12 percent); blindness (2.82 percent); hemiparesis (1.83 percent); paraparesis (1.70 percent); multiple disabilities (1.20 percent); tetraparesis (0.99 percent); cerebral palsy (0.98 percent); hemiplegia (0.92 percent); intellectual disability (0.71 percent); tetraplegia (0.47 percent); dwarfism (0.35 percent), and others.

plus one as the dependent variable and taking its natural logarithm. Column (4) excludes state- and industry-specific trends and shows similar results. Columns (5) and (6) replace the ordinary least square estimator with a conditional fixed-effect Poisson model to account for count data. The Poisson method corroborates the magnitude of employment effects for people with disabilities (58.9 percent) and the lack of impacts for workers without disabilities. As discussed in Section 5.1.1, Columns (7) and (8) consider more local specifications with closer bandwidths around the threshold of 100 employees, whereas Columns (9) and (10) exclude firms close to it. I find similar estimates across sample restrictions.

5.2 The Wage Effects

5.2.1 Empirical Strategy

While the conclusion that AA quotas led to higher employment for the targeted group is consistent with the literature, there is a dearth of evidence of the impacts of quotas on workers' outcomes, including wages. To further understand the effects on workers' outcomes, I estimate the following specification:[27]

$$w_{ijt} = \sum_{k=-6}^{k=12} [\beta_k^{Quota} \times \mathbf{1}(t_j = t^* + k) \times Quota_{j,-1} + \theta_k \times \mathbf{1}(t_j = t^* + k)] + \alpha_j + \alpha_t + X_{jt}\gamma + X_{ijt}\delta + \varepsilon_{ijt}, \tag{6}$$

in which subscripts i, j and t stand for worker, firm and quarter-year; $\mathbf{1}(t_j = t^* + k)$ are dummies indicating an event in quarter-year k relative to the quarter-year t^* in which the firm is inspected; $Quota_{j,-1} = \mathbf{1}(\text{Emp}_j \geq 100)$ is an indicator variable for firms under the AA quota for having at least 100 employees in the quarter-year prior to inspection; α_j are firm fixed effects; α_t are quarter-year fixed effects; and the vectors X_{jt} and X_{ijt} represent firm- and worker-level controls. Firm-level controls consist of state- and industry-specific trends. Worker controls include individual characteristics available in the RAIS data, such as gender, race, educational level fixed effects, age, and square age, along with occupation group fixed effects. Standard errors are clustered at the firm level.

Similar to Equation (4), the post-event coefficients—β_k^{Quota}—capture the dynamics impacts of

[27] In addition to the event-study analysis, I also perform a difference-in-differences analysis in which I pool pre- and post-inspection quarters and estimate the change in wages considering the following model:

$$w_{ijt} = \alpha_j + \alpha_t + \tilde{\beta} \times Post_t \times Quota_{j,-1} + \alpha_j + \alpha_t + X_{jt}\gamma + X_{ijt}\delta + \varepsilon_{ijt}, \tag{5}$$

in which subscripts and the set of controls and fixed effects are the same as in Equation (6), and $Post_t \times Quota_{j,-1}$ is an indicator variable equal to 1 for all quarters after inspection in firms under AA quota. As before, standard errors are clustered at the firm level.

the AA quota relative to the quarter-year before the labor inspection. Identification assumptions of Equation (6) rely on the timing of labor inspection being uncorrelated with the outcomes of interest, *conditional* on the set of controls. The key identifying assumption is that the wage outcomes for workers in firms with and without AA quota requirement, representing treatment and control firms, would have followed parallel trends in $k > 0$ if no inspection had occurred for firms under the AA quota. I test this assumption by assessing whether the pre-event coefficients of interest are statistically indistinguishable from zero.

Sample and Summary Statistics To examine the wage effects, I use the natural logarithm of hourly wages as the main outcome. This outcome combines information on contracted monthly hours and average wages.[28] In order to obtain the sample of workers, I recover all individuals that worked full time at the same set of firms from the firm-level analysis spanning the period from six quarters before to twelve quarters after the inspection. Using worker-level data is appropriate because the impacts at the firm level could be confounded by compositional changes rather than reflect changes in wages for similar workers. In addition, I construct the worker-level sample at the quarterly frequency, which offers two advantages.[29] This sample is comparable with the firm-level sample, enabling a closer examination of the dynamics effects. The second advantage is to enlarge the sample size, increasing statistical power. Statistical power is an important concern in this context since people with disabilities are vastly underemployed. The interpretation of the results remains unchanged when considering annual frequency.

I present summary statistics during the quarters before and after inspections for workers from both treated and control firms. Table E6, Appendix E, indicates that both groups of workers are similar along observable characteristics prior to inspections, including wages, disability, gender, race, education, occupation, location, and economic sector. Considering the pre-inspection period, nearly 0.4 (0.3) percent of control (treated) workers have a disability, earn about 11.34 Brazilian *reais* (11.46 Brazilian *reais*) as hourly earnings, 66 (65) percent are male, 67 (69) percent are white, 10 (10) percent have a college degree, and 66 (66) percent have blue collar jobs.

5.2.2 Worker-Level Results

To gauge the impact of the AA quota on workers' wages, I estimate Equation (6), which directly compares workers from firms under the AA quota to those unaffected by the regulation, before and

[28]This measure of wages also contains other forms of monetary work compensation, including overtime premiums, bonuses, commissions, and other benefits mandated by law.

[29]Until 2015, information on wages from the RAIS data are reported at the annual frequency. I transform them into quarterly data by combining information on earnings with hiring and separation dates.

after inspection. Figure 4 illustrates the dynamics of wages around inspection shocks separately for workers with and without disabilities. The pre-event coefficients are statistically equal to zero, validating my empirical strategy. As expected, the confidence intervals for persons with disabilities are larger due to the smaller sample size.

Table 5 displays the immediate ($k = 0$), short run ($k = 6$), long run ($k = 12$) impacts, together with the aggregate impacts. In the first quarters following inspections, the estimates for both groups of workers are statistically insignificant. Over time, the quarterly wage growth does not change for workers without disabilities, which can be interpreted as the policy having limited consequences on non-targeted groups. On the other hand, wage growth becomes slower for people with disabilities at firms under the AA quota. The estimates imply that these workers experience 6 percent slower wage growth relative to the baseline wage growth rates (Column (4) of Table 5). Including firm and quarter fixed effects requires firms from treatment and control groups to have at least one worker with disabilities prior to inspections to estimate the coefficient of interest for people with disabilities.

Table 5 also investigates whether the results are driven by incumbent workers or new hires (Columns (5) and (6)). Figure D5, Appendix D, plots the estimates for the subset of individuals who are hired in each quarter-year of the sample and shows no evidence of differential wage growth. Figures 4(c) and 4(d) indicate that incumbent workers with disabilities drive the wage effects.[30] The lack of pass-through to new hires could be explained by labor contract rigidities or labor market institutions, such as wage floors and minimum wage.[31] As such, firms adjust through incumbents' wages from the targeted group with slower wage growth. The results point to an unintended consequence of mandated employment: despite the reduction in inequality at the *hiring* level through higher employment opportunities, firms can adjust to mandated employment through lower wage growth, exacerbating *within*-firm inequality *between* groups and, to some extent, reversing the goal of the policy.

One concern with my baseline estimates is that, on average, workers with disabilities are less educated, less experienced and more likely to be employed in low skill occupations, implying that the wage results could reflect differences along these dimensions and, as a result, in productivity.

[30] In particular, I estimate a modified version of Equation (6):

$$w_{ijt} = \sum_{k=-6}^{k=12} [\beta_k^{Quota} \times \mathbf{1}(t_j = t^* + k) \times Quota_{j,-1} + \theta_k \times \mathbf{1}(t_j = t^* + k)] + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt}, \tag{7}$$

in which the subscripts and the remaining variables are the same as in Equation (6); and α_i are worker fixed effects. Including worker fixed effects ensures that the coefficients of interest, β_k, capture the impact on wages *within* workers. The findings are robust to restricting the sample to workers in the same firm over the analysis period.

[31] The heterogeneity analysis across different levels of corporate hierarchy indicates that the earnings effects are concentrated in white-collar rather than blue-collar jobs, consistent with blue-collar jobs being more constrained by labor market institutions.

Including worker controls does not affect the results (Column (2) of Table 5). As a sanity check, I also report estimates using two re-weighting methods to reduce observational dissimilarities and allow workers with and without disabilities to be similar along several pre-inspection characteristics: gender, race, age, squared age, education, and occupation. Figure 5(a) presents coefficients using inverse propensity score weights computed from this set of characteristics, whereas Figure 5(b) shows estimates using the entropy-balancing weights from Hainmueller (2012) to ensure balance across the same characteristics. I note that the results are robust to re-weighting methods, alleviating concerns related to dissimilarities in observable characteristics across disability status.

Magnitude. To better understand the magnitude of the reduced wage growth, I compare it with other contexts. For instance, a burgeoning literature studying the relationship between employer concentration and wages has documented that increasing labor market concentration is associated with wage reductions ranging from 2.9 to 26 percent (Arnold (2019), Azar et al. (2022), Benmelech et al. (2022), Prager and Schmitt (2021), Qiu and Sojourner (2019), Rinz (2022)). The displacement literature has documented earnings losses across countries that range from 6 to 42 percent, though estimates from the lower end are far more common (Jacobson et al. (1993), Couch and Placzek (2010), Lachowska et al. (2020), Davis and Von Wachter (2011), Bertheau et al. (2022)). In the Brazilian context, Bhalotra et al. (2021) find a 42 percent decline in work income up to three years after displacement caused by mass layoffs. My estimates are about one-seventh of the expected earnings losses from displacement.

Effects on Additional Worker Outcomes. Figure 5 and Table 6 display results for other labor market outcomes. I document the impacts on the intensive margin of employment measured by the number of hours specified in the employment contract and the likelihood of part-time employment. Although the RAIS data do not provide the actual number of hours worked, contracted hours and part-time status are informative about adjustments through intensive margins. Figures 5(a) and 5(b) corroborate the lack of evidence supporting such responses.

I also analyze the effects on turnover and promotion. Figure 5(c) shows that the probability of staying at the firm is higher for incumbents with disabilities in firms under AA quota in the first quarters following inspection and then gradually dwindles. To measure the impacts on the probability of internal promotion, I compute the average wages for each 6-digit occupation cell after regressing log hourly earnings on 6-digits occupation and individual fixed effects in a random sample of 20 percent of workers in the private sector. With the occupation effects in hand, I define promotion as an indicator variable equal to one if the worker switches into an occupation that pays higher wages at the same firm relative to the previous quarter. The treatment effect from Column

(3) of Table 6, albeit relatively noisy, points to a decrease in the likelihood of promotion of 1.4 percentage points for workers with disabilities in firms under the AA quota relative to those in firms without the AA quota. I do not find similar patterns for workers without disabilities.

5.2.3 Heterogeneity and Mechanisms

Using observational data and qualitative evidence from a survey conducted with firms (see Appendix F for further details) together with several heterogeneities, this section provides suggestive evidence pointing to discrimination as a key driver behind the worker-level results. I also examine to what extent the main results could be rationalized through alternative explanations, with the limitation that the findings only allow a suggestive glimpse into mechanisms. Which mechanism ultimately explains my findings is hampered by data constraints and left for future work.

Discrimination. A large body of literature has documented employer discrimination against people with disabilities using observational evidence (Baldwin and Johnson (1994), Baldwin and Johnson (2006)) or experiments (Baert (2016), Ameri et al. (2018)). Discrimination can can be taste-based (Becker (1957)) or statistical (Phelps (1972), Arrow (1973), Aigner and Cain (1977)). Models of statistical discrimination assume that employers cannot directly observe workers' skills. Instead, they observe signals to infer workers' skills and are less able to interpret signals of workers from a minority group. In a dynamic setting with career progression, Bjerk (2008) shows that, if two groups differ in average skill level or in frequency they can signal their skills at lower level jobs, similarly skilled workers from distinct groups can have different career progressions. Members from the minority group need to accumulate more positive signals to get challenging tasks or promoted, leading to unequal opportunities at the workplace. Lehmann (2011) shows that this pattern can be the result of an affirmative action policy, in which firms recruit more workers from the minority group, but managers require more positive signals to assign them to the more challenging tasks.[32]

In my setting, AA quotas induce firms to lower hiring standards to recruit more workers with disabilities (Coate and Loury (1993), Moro and Norman (2003), Fang and Moro (2011)). Both observational and survey evidence suggest that the average skill level declines with an increase of less educated workers among the group of persons with disabilities. For instance, Figure D3,

[32] Bjerk (2008)'s "sticky-floor" model was originally used to explain the underrepresentation of women and minorities in top jobs in the absence of discrimination with respect to promotion. In another dynamic model of statistical discrimination without affirmative action, Fryer Jr (2007) theoretically shows that, once members from a group with negative stereotypes overcome discrimination at the initial stage and are hired, the successful members from this group are more likely to be promoted due to a "belief flipping". In this scenario, there is a general pessimism about a group, though optimism about the successful members of this group. This model would explain, under some conditions, overrepresentation of minorities in the highest jobs. Lehmann (2011)'s model explains the increase of black workers in law firms at the hiring stage and their underrepresentation as partners.

Appendix D, reveals that firms under the AA quota hire more disabled workers without a college degree. Survey responses also indicate that firms under AA are more likely to report not being able to find qualified people with disabilities or differences in productivity and management time between workers with and without disabilities as challenges for the company.

To provide an indirect test for whether employers require more positive signals to assign better task assignments or promote without on-the-job data, I examine whether the wage effects are heterogeneous across two dimensions along which workers can send stronger signals of their skills: educational degree and frequency of communication with supervisors and peers. I obtain a measure of frequent communication after matching occupations from RAIS data to O*NET database, which ranks occupations requiring more on-the-job interactions.[33] Table 7 reveals that the wage impacts are driven by workers without college education and in jobs with less interpersonal relationships. In contrast, I find no significant impacts for workers with a college degree and more on-the-job interactions. Regardless of the final mechanism, the fact that group differences are sustained points to the existence of multiple equilibria under affirmative action (Coate and Loury (1993)).

Becker (1957)'s theory of taste-based discrimination posits that employers have a negative animus towards people with disabilities regardless of productivity considerations. I note that two pieces of evidence seem inconsistent with this theory as an explanation for wage growth slowdowns among incumbent workers with disabilities. First, an affirmative action policy would make firms hire more qualified workers with disabilities. On the contrary, I find that firms recruit more workers with lower educational levels. Second, because the empirical findings are driven by incumbents with disabilities, the taste-based theory implies that employers have developed some distaste for workers with disabilities over time. This seems unlikely in light of evidence that tastes are not easily malleable in the short-term (Beaman et al. (2009)). While my empirical results are consistent with the discrimination channel, the lack of on-the-job data and clean experiments makes it difficult to provide conclusive statements about whether the discrimination is taste-based or statistical.

Alternative Mechanisms. I also investigate other possible mechanisms that could explain the worker-level results. The goal of this exercise is not to disprove that these other channels play a role in the results. Instead, I provide suggestive evidence that they are unlikely in my setting.

One possible explanation is that firms may incur sizable and irreversible fixed costs due to the AA quota. For instance, employers may experience increases in workplace accommodation

[33] The O*NET database describes and ranks a variety of work activities, including skill requirements. I classify jobs below and above the median of communicating with supervisors and peers, which is defined as "providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person" as those that workers can signal their abilities more frequently. The results are not sensitive to the choice of measure of interpersonal relationships since I find similar results for other work activities.

costs (e.g., assistive technologies) or investments in capital (e.g., specialized employment agencies) to improve screening of candidates with disabilities (Miller (2017)).[34] As a result, employers may offset the extra irreversible fixed costs by lowering wage growth for workers with disabilities. Several pieces of evidence reject this explanation. Incumbents were hired before the inflow of new hires, suggesting that, if these costs exist, they were incurred before the new hires. The survey indicates that accommodation costs and screening technologies play a very minor role.[35] The lack of evidence supporting that firms provide accommodations or other amenities also implies that the theory of compensating differentials (Rosen (1974), Rosen (1986)), in which firms may provide lower wages premium to compensate for positive amenity shocks, is an unlikely explanation.

In line with the fixed costs theory, rent-sharing models indicate that the AA quota might affect firm rents, impacting the wages of workers, especially stayers (e.g., Stole and Zwiebel (1996)), Cahuc et al. (2008), Caldwell and Harmon (2019)), Jäger and Heining (2019)). Such models are consistent with lower wage growth. However, ancillary evidence that firm exit and wages of workers without disabilities remain unaffected, along with robustness from re-weighting methods, suggests that reduced rents are unlikely drivers of the results.

Retaliation against employees due to whistleblowing could also explain the findings. For example, firms might believe that employees are engaged in complaints against them. First, the administrative data point that 42.07, 19.62, 16.67, and 12.56 percent of the firm-level sample have non-mutually exclusive violations related to formal registration, severance pay, working hours, and days off. These statistics indicate that it is unlikely that firms infer that incumbents with disabilities are the whistleblowers. Second, the survey found that 41.67 percent of respondents thought that inspections were likely triggered by employees. When asked who they think made these complaints, incumbents with disabilities are never mentioned.

[34] Workplace accommodation costs are frictions that have received a lot of attention in the literature on labor market participation for people with disabilities (Oi (1991), Rosen (1991), Acemoglu and Angrist (2001)). Building on seminal Phelps (1972)' model of statistical discrimination, Miller (2017) argues that an AA quota may induce employers to invest more in screening capital. When subject to an AA quota, employers prefer to hire the most productive candidates from the benefited group. A potential drawback is that employers only observe a noisy signal for each candidate's productivity. The screening model states that firms can invest in screening capital, such as specialized human resources personnel and employment agencies, to improve screening of minority candidates, which can also be interpreted as irreversible fixed costs (Holzer and Neumark (2000)).

[35] Only 8 percent of firms in the survey provided workplace accommodations to the last hire with disabilities. None of the respondents reported that it cost more than hiring someone without disabilities for the same position. As a benchmark, in a survey about workplace accommodations conducted by the Job Accommodation Network (JAN) and sponsored by the Department of Labor in the US since 2004, 56 percent of firms reported that the accommodations needed by employees did not cost anything; 39 percent had a one-time cost; and only 5 percent said the accommodation resulted in annual costs. The median expenditure on accommodations with a one-time cost was \$500. When asked about the costs incurred to accommodate an employee with disabilities in addition to what they would have paid for an employee without in the same position, the median answer given by employers is \$20 (Job Accommodation Network (2020)).

6 Implications for Welfare

Thus far, the empirical results point to employment and wage consequences of enforcing AA quotas. To explore potential normative implications of my findings for aggregate welfare, I introduce a simple model of an enforcement of AA quotas with imperfect compliance. Following insights from the literature on law enforcement and disability insurance (Diamond and Sheshinski (1995), Burlando and Motta (2016), Haller et al. (2020)), the model allows me to characterize the welfare impacts of increasing enforcement of AA quotas for firms, workers, and government. I then provide more context by discussing the implications for each group, and conditions under which the policy can be welfare enhancing.

6.1 Welfare Framework

Model Setup. Consider a simple one-period model with populations of firms and people with disabilities of mass unity. Furthermore, consider the decision to comply with the AA quota regulation for a representative firm. The firm derives disutility from hiring a worker with disabilities, denoted by $\sigma \sim F(\cdot)$, with pdf $f(\cdot)$, which can also capture taste for non-compliance. If σ is small, the firm fully complies with the AA quota and obtains profit or surplus specific to people with disabilities $MRPL_d - w - \sigma$, in which $MRPL_d$ is the marginal revenue product generated by the employee with disabilities and w is the wage paid to the same employee.[36] If σ is sufficiently large, the firm initially does not comply with the regulation and incurs in the risk of detection by the government. With probability $p(\sigma)$, in which $p'(\sigma) > 0$, the government detects non-compliance. In this case, the firm faces the choice between complying with the regulation and hiring a person with disabilities, $M\tilde{RPL}_d - w - \sigma$, or being sanctioned for delinquency and getting fined by an amount of F.[37] With probability $1 - p(\sigma)$, there is no detection and firm profit does not change.

The firm's choices can be translated into individual payoffs for people with disabilities. When a person with disabilities is employed, she enjoys utility $u(w - \tau)$, in which w represents the wage she earns, τ is the lump-sum tax she pays to the government while employed, and the utility function u is increasing and concave. In case of unemployment, she claims welfare benefits b from the government and gets utility $v(b)$, in which the utility function v is also increasing and concave. Figures G1 and G2, Appendix G, illustrate the choices.

In addition, let $\sigma^C = MRPL_d - w + p(\sigma^c)F$ denote the threshold value of σ indicating indifference

[36] For simplicity, I take wages as given. This is consistent with institutional constraints, such as minimum wages, wage floors, and on-the-job wage rigidity.

[37] There is a small change in notation in the marginal revenue product of labor to incorporate potential additional disutility from compliance after detection, such as follow-up checks from the government, bureaucratic hassle, etc., or, more broadly, potential costs to accommodate a worker with disabilities.

between compliance and delinquency. Firms with $\sigma \leq \sigma^C$ initially comply with the regulation while those with $\sigma > \sigma^C$ are delinquent. Let $\sigma^F = M\tilde{RPL}_d + F - w$ denote the threshold value indicating indifference between compliance and fine payment conditional on detection. Firms with $\sigma \leq \sigma^F$ prefer to hire a worker with disabilities after detection while those with $\sigma > \sigma^F$ pay the fine. Lastly, assume that $\sigma^F > \sigma^C$ holds.

The government does not observe σ. Instead, the government observes an imperfect enforcement level, σ^*, and attempts to increase employment of people with disabilities by increasing enforcement (e.g., labor inspections), affecting the probability of detection, $p(\sigma^*)$.[38] I next define the surplus levels for firms and people with disabilities and outline the government budget.

Firms. Given w, the producer surplus associated with hiring people with disabilities can be expressed as:

$$\begin{aligned} \Pi(\sigma^*) = \int_0^{\sigma^c} [MRPL_d - w - \sigma]\, f(\sigma)\, d(\sigma) + \int_{\sigma^c}^{\sigma^F} p(\sigma^*)[M\tilde{RPL}_d - w - \sigma]\, f(\sigma)\, d(\sigma) + \\ \int_{\sigma^F}^{1} p(\sigma^*)[-F]\, f(\sigma)\, d(\sigma) + \int_{e^c}^{1} (1 - p(\sigma^*))\, f(\sigma)\, d(\sigma), \end{aligned} \tag{8}$$

in which the right-hand side sums up the surpluses under different scenarios: when there is compliance from the beginning (first term); when the firm complies with the AA quota regulation after detection (second term); when the firm decides to pay a fine after detection (third term); and when both non-compliance and non-detection occur (fourth term).

People with Disabilities. Given w, τ and b, the total welfare of people with disabilities can be written as:

$$\begin{aligned} V(\sigma^*) = \int_0^{\sigma^c} u(w - \tau)\, f(\sigma)\, d(\sigma) + \int_{\sigma^c}^{\sigma^F} p(\sigma^*) u(w - \tau)\, f(\sigma)\, d(\sigma) + \\ \int_{\sigma^F}^{1} p(\sigma^*) v(b)\, f(\sigma)\, d(\sigma) + \int_{\sigma^c}^{1} (1 - p(\sigma^*)) v(b)\, f(\sigma)\, d(\sigma), \end{aligned} \tag{9}$$

in which the right-hand side sums up the utilities of different profiles of people with disabilities integrated over the distribution of σ: employed due to initial compliance (first term); employed due to compliance after detection (second term); recipients of welfare benefits in case of fine payment

[38] Another policy lever available to a government as part of an enforcement scheme is fines. I assume that the government takes the fine F as given. This assumption is consistent with little variation in the value of fines over time.

after detection (third term); and recipients of welfare benefits due to both non-compliance and non-detection (fourth term).

Government. The total revenues raised by the government can be written as:

$$
\begin{aligned}
R(\sigma^*) = \tau \int_0^{\sigma^c} f(\sigma)\, d(\sigma) + \tau \int_{\sigma^c}^{\sigma^F} p(\sigma^*)\, f(\sigma)\, d(\sigma) + F \int_{\sigma^F}^{1} p(\sigma^*)\, f(\sigma)\, d(\sigma) \\
-b \int_{\sigma^F}^{1} p(\sigma^*)\, f(\sigma)\, d(\sigma) - b \int_{\sigma^c}^{1} (1 - p(\sigma^*))\, f(\sigma)\, d(\sigma),
\end{aligned}
\tag{10}
$$

in which the right-hand side accounts for the taxes raised from employment, the fines raised after detection, and the welfare benefits paid to the unemployed. The government also incurs the cost of enforcement, defined as $C(\sigma^*)$.

Welfare Effects of Enforcing AA Quotas. I assume that the government also uses a higher enforcement level to raise additional fiscal revenues $R(\sigma^*)$ (e.g., to increase the provision of public goods). The government sets enforcement level σ^* to maximize the following social welfare function:

$$
W(\sigma^*) = \Pi(\sigma^*) + V(\sigma^*) + R(\sigma^*) - C(\sigma^*). \tag{11}
$$

Under standard regularity conditions, Appendix G shows that the welfare effect from raising enforcement level σ^* can be written as:

$$
W'(\sigma^*) = \underbrace{M_C[M\tilde{RP}L_d - w]}_{\text{marginal firm cost}} + \underbrace{M_C[u(w-\tau) - v(b)]}_{\text{marginal welfare benefit for PwD}} + \underbrace{M_C[\tau + b]}_{\text{marginal revenue benefit}} - \underbrace{C'}_{\text{marginal cost of enforcement}}, \tag{12}
$$

in which $M_C \equiv \int_{\sigma^c}^{\sigma^F} \frac{\partial p(\sigma^*)}{\partial \sigma^*} f(\sigma)\, d(\sigma)$ captures the mechanical increase in employment for people with disabilities due to increased enforcement. Equation (12) illustrates four key objects that govern the effects of increasing enforcement on social welfare. First, the change in producer surplus, which depends on the wedge between marginal revenue products of people with disabilities, $M\tilde{RP}L_d$, and their wages, w. Second, the change in surplus for people with disabilities from working, $u(w - \tau)$, relative to their reservation utility from receiving welfare benefit from the government, $v(b)$. Third, when the government has revenue-maximizing reasons, the extra revenues coming from income tax τ

and welfare benefits savings b due to higher employment. Fourth, the marginal cost of enforcement (e.g., administrative costs). I note that, since the empirical results show that people without disabilities are unaffected, there is no welfare change for them. In contrast, raising fiscal revenues with increased employment to provide public goods can increase welfare.[39]

This framework abstracts from other factors that can contribute to the aggregate welfare. For instance, I do not account for crowd out from public to private health care (Paim et al. (2011)) or better health conditions (Sullivan and Von Wachter (2009)) and lower criminal involvement (Deshpande and Mueller-Smith (2022)) due to increased employment as potential social benefits. I also do not consider welfare losses to workers without disabilities, distortions in the production function, or moral hazard as potential social costs. Because the reduced-form analysis shows little evidence that enforcement of AA quotas affected workers without disabilities or firm outcomes, the social benefits are underestimated. Another limitation is that the social welfare function assumes that people with disabilities have the same social welfare weights as firms. The fact that quota policies are prevalent across the world suggests that governments put more value on the welfare of people with disabilities. Calculating the social welfare weights is beyond the scope of this paper and an important area for future work.

6.2 Implications and Discussion

Firms. The firm-level analysis in Section 5.1.2 finds no evidence that firms under AA quotas are more likely to exit the formal sector, decrease wages for workers without disabilities, or bunch below the regulation threshold. These evidence suggest that firms do not experience lower profits. To further support the lack of changes in profits without additional data on firm outcomes, I propose a simple discrete choice framework that provides a tractable closed-form solution to estimate the marginal revenue product of new hires with disabilities with the available data. Another motivation for this exercise is the lack of evidence of estimates of marginal revenue product of workers with disabilities in the literature.

Conditional on inspection and detection, non-compliant firms have two choices available: they can choose either to pay fines, or abide by the AA quota regulation by hiring additional workers up to the requirement. If it chooses to pay fines, firm i gets utility $U_{i,f} = -F_i$, in which F is the amount of fines. If the firm chooses to hire new workers to comply with the regulation after an inspection, it obtains utility $U_{i,c} = \gamma(MRPL_d - w_i) - \epsilon_i$, in which γ is the amount of new hires

[39]Fines represent a lump-sum transfer from firms to the government. Wage adjustments to incumbent workers, under a linear utility function, also represent a transfer from people with disabilities to firms. In theory, the marginal producer cost can account for potential fixed costs to accommodate workers with disabilities. As discussed in Section 5.2.2, both the administrative and survey data point to little evidence of fixed costs. Therefore, there is no change in the producer surplus due to fixed costs in the welfare evaluation.

necessary to become compliant, $MRPL_d$ is the marginal revenue product of people with disabilities, w_i is the wages paid to disabled employees, and ϵ_i is a distaste parameter for hiring workers with disabilities such that $\epsilon_i \sim \mathcal{N}(0,\, \Sigma_i^2)$.

Define the probability that a firm chooses compliance after inspection as $P_{i,c} = \Pr(U_{i,c} \geq U_{i,f})$. It can be rewritten as:

$$P_{i,c} = \Phi(\beta_0 + \beta_1 w_i + \beta_2 F_i), \tag{13}$$

in which $\beta_0 \equiv \frac{\gamma MRPL_d}{\Sigma_i}$; $\beta_1 \equiv -\frac{\gamma}{\Sigma_i}$; and $\beta_2 \equiv \frac{1}{\Sigma_i}$. Equation (13) is a probit model that can be estimated via maximum likelihood. An alternative functional form for the distaste parameter following a logistic distribution leads to similar conclusions. The marginal revenue product can be expressed as a function of estimates of β_0 and β_1 because $M\hat{RPL}_d = -\frac{\hat{\beta_0}}{\hat{\beta_1}}$.[40] Table 8 indicates that estimates of the ratio between estimated marginal revenue product of labor and average wages are around 1.10-1.26. At best, these estimates reject that marginal revenue products of people with disabilities fall below their wages.

People with Disabilities. I next examine the changes in surplus for people with disabilities. The job surplus depends on workers' value of being employed under wage contract w, $u(w)$, relative to their unknown value of the outside option, $v(b)$. In competitive labor markets, workers get paid for their marginal product, implying a zero surplus from employment relationships. Nonetheless, the high involuntary unemployment rates (Column (2) of Table A1, Appendix A) and the presence of binding minimum wages and union wage floors (Engbom and Moser (Forthcoming)) are inconsistent with perfectly competitive labor markets.[41] Rents from employment relationships are thus likely to be positive for workers with disabilities.

If the surplus from employment is positive for people with disabilities, which labor market frictions can explain that many firms do not voluntarily hire these workers without quotas? Minimum wages and union wage floors are plausible candidates. Figure G3, Appendix G, indicates that the minimum wage is more binding among workers with disabilities than among workers without disabilities. This discrepancy could hint, for instance, that firms do not hire people with disabilities because their marginal product is below the minimum wage. However, this hypothesis is inconsistent

[40] I use the fine schedule established in Ordinance 1,199/2003 from the Ministry of Labor to calculate the amount of fines that newly compliant firms would have paid if they choose non-compliance. For the firms that pay fines rather than hire disabled workers, the predicted value of wages is drawn from the distribution of wages of the new hires without disabilities since firms are not allowed to offer distinct wages to new workers from the same position and tenure. In addition, standard errors are bootstrapped from Equation (13). More precisely, I construct 1,000 samples and repeat estimation for each sample, generating the standard deviation of these bootstrap iterations.

[41] In 2010, the unemployment rates for people reporting to live with some and severe difficulty are around 10 and 14.5 percent, larger than the unemployment rate of 6.4 percent for those without disabilities.

with previous empirical findings.

Instead, the findings are very consistent with discrimination. A large body of literature has documented employer discrimination against people with disabilities using observational or experimental evidence ((Baldwin and Johnson (1994), Baldwin and Johnson (2006), Baert (2016), Ameri et al. (2018)). In fictitious audit experiments randomizing information on disabilities that do not limit productivity in administrative positions, Ameri et al. (2018) find that candidates with disabilities receive way fewer callbacks for interviews than similar candidates without disabilities in the United States. The vignette experiment in the survey with HR personnel reveals similar a similar pattern in Brazil: respondents are significantly less likely to express interest in hiring a candidate with disabilities.[42] Conceptually, discrimination explains why employers do not hire people with disabilities even when their marginal products are equal to or above their wages. Under these circumstances, hiring quotas can increase employment for people with disabilities without displacing workers without disabilities or shutting firms down.

Without taking a stance on the sources of labor market frictions, I translate the surplus gain of enforcing quotas for people with disabilities into a money metric gain from employment. I err on the side of caution and make additional restrictive assumptions. First, I restrict the gain to occur only in the first year of an employment spell. Second, the marginal welfare benefit is assessed assuming a linear utility function. It implies using the income flow of switching from welfare benefits to employment as the welfare gain. Third, I also account for the opportunity cost of a full-time job due to lost leisure. Following Mas and Pallais (2019), I assume a value of non-work relative to the wages of 0.58. Considering the reduced-form estimates, the (lower bound) estimated marginal welfare benefit of each inspection is net positive: about 372.65 Brazilian *reais*. A detailed description of the calculations can be found in Appendix G.

Government. On the fiscal side, the relevant objects are the marginal cost of enforcement and the marginal fiscal revenue benefit. While there are no data available on detailed spending on each inspection, the average cost of inspections is an upper bound for the marginal cost of enforcement. The data on total expenditures on enforcement capacity reveal that the average cost of a labor inspection is around 99 Brazilian *reais*. Compared to the marginal revenue benefit of 668.34 Brazilian *reais* from each inspection, my results demonstrate unambiguous positive impacts. In addition,

[42]In the survey, respondents are assigned to a vignette describing a big fictitious consultancy that would like to hire someone for an entry-level job to do routine clerical and organizational tasks. I introduce a 22-year-old man who finished high school, has flexibility, proactivity, and good organization skills, and interacts well with people. For some respondents, I randomize the information that the man has a bilateral hearing loss. I then ask respondents to rate, on a four-point scale, in which 1 is "unlikely" and 4 is "very likely", how likely they think that the company would be interested in hiring him and that he would accept the job. Table F1, Appendix F, reports the findings.

disregarding the marginal revenue benefit preserves the conclusion of net positive impacts since the marginal welfare benefit for people with disabilities exceeds the average cost of enforcement.

Additional Discussion. These results together suggest that, in the presence of imperfect competition and frictions in the labor market, firms may be inefficiently small in equilibrium, and enforcing modest affirmative action hiring quotas redistributes jobs to people with disabilities and induces aggregate welfare gains. I note that, although the data reject that the marginal revenue products of people with disabilities fall below their wages in this context, an important caveat is that I am not able to directly test whether workers with and without disabilities have the same marginal product. Recent literature has found substantial average wage markdowns, with the ratio of workers' marginal revenue product of labor to their wage ranging from 1.40 to 2.13 in other contexts (e.g., Amodio and De Roux (2021), Berger et al. (2022), Yeh et al. (2022)). In Brazil, Felix (2021) finds a ratio of 2 during the 1990s.[43] Comparing my estimates to what other papers have documented, it might be tempting to conclude that people with disabilities are less productive than those without disabilities. The wide range of estimates in the literature, however, suggests great sensitivity to the context. To my knowledge, no recent research has investigated the differences in wage markdowns for workers with and without disabilities, let alone within the same context, and this is an important area for future work.

7 Conclusion

This paper provides a novel and comprehensive assessment of the redistributive implications of enforcing affirmative action quotas for one of the most disadvantaged yet understudied groups: people with disabilities. Exploiting the timing of a reform in Brazil that raised enforcement of a new affirmative action hiring quota regulation, my market-level analysis indicates that people with disabilities living in local labor markets more exposed to the reform experience larger increases in formal sector employment and earnings than those in less exposed markets. Leveraging variation in enforcement through inspections across firms, I document that the increase in employment induced by hiring quotas does not come at a discernible cost to other workers in terms of wages or employment or to firms, and raises fiscal revenues. My results indicate that, in labor markets under imperfect competition, enforcing modest hiring quotas generates aggregate efficiency gains and, therefore, constitutes a promising pathway for countering the low levels of employment for the disadvantaged.

[43] Because information on workers with disabilities in the formal sector only started to be collected in 2003, it is not possible to compute average wage markdowns across disability status using Felix (2021)'s approach, which focuses on the pre-liberalization (the 1990s) period.

This conclusion points to several new directions for future work. First, there might be strong complementarities between quotas and wage subsidies, amplifying the effects of these regulations. Second, aggressive hiring quota regulations and rigid enforcement structures might create different consequences that I do not capture here (e.g., Peck (2017)). Third, I do not exploit the optimal share of mandated employment that maximizes the efficiency gains of quotas in settings with imperfect competition. Each direction invites more research to be done, since improving labor market prospects for the disadvantaged remains a policy priority in many countries.

This paper offers several other policy-relevant findings. The analysis points to strong complementarities between quota regulations and enforcement capacity. In light of extensive evidence that firms do not actively meet the minimum percentage of quotas, including in the United States for federal contractors who are required to set a goal of having 7 percent of their workforce composed of persons with disabilities, my results suggest that investing in compliance seems attractive from a redistributive perspective. On the other hand, evidence that incumbent workers with disabilities are negatively affected also suggests that firms have some ability to redistribute the costs across and within workers, contributing to the rise of workplace inequality.

Disability hiring quotas might also generate other positive externalities. For instance, firms fostering an inclusive environment might benefit from higher diversity in teams of workers and complementarities between workers in production. Hiring quotas can promote additional social benefits, such as better health conditions and lower mortality rates due to employment, access to better health services due to crowd out from public to private care, and lower criminal involvement. These possible social benefits are left for future work. Therefore, this paper should be viewed as an initial step toward characterizing the social benefits of hiring quotas.

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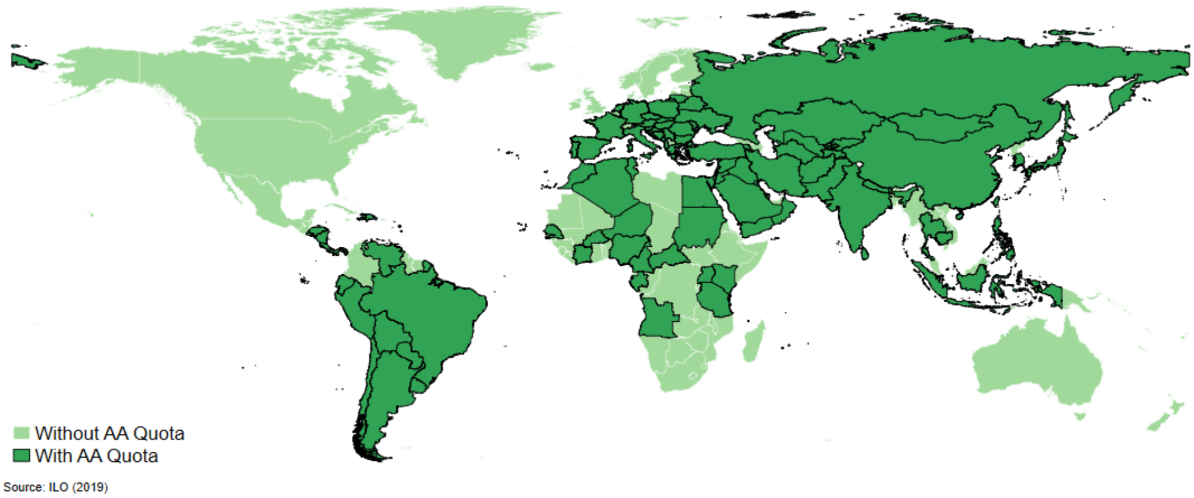
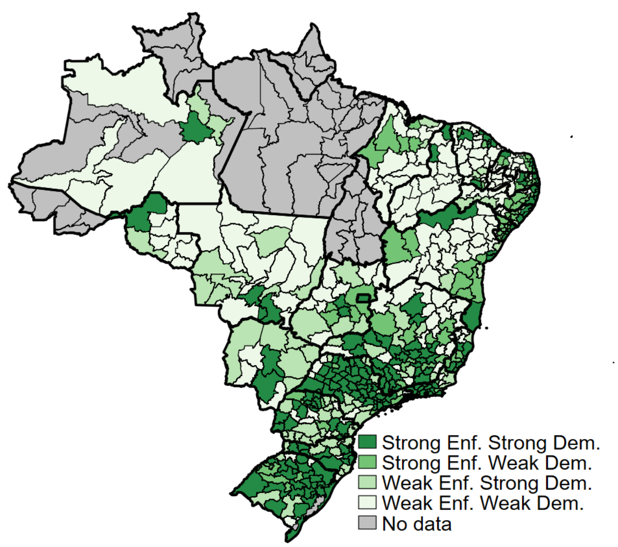
Figure 1: Countries with Hiring Quotas for People with Disabilities



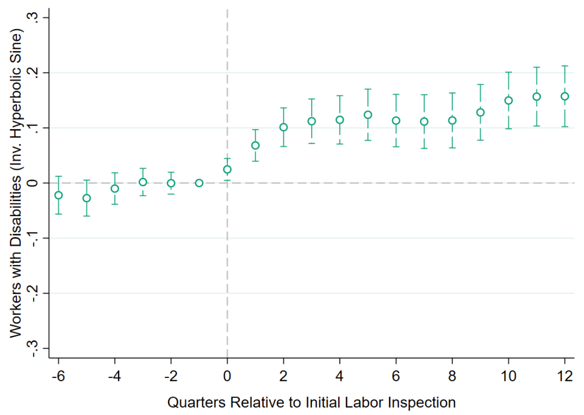
Note: This map illustrates the prevalence of affirmative action hiring quotas for people with disabilities, which are implemented in more than 100 countries. Source: ILO (2019).

Figure 2: Cross-Market Variation: Interaction between Potential Demand & Enforcement

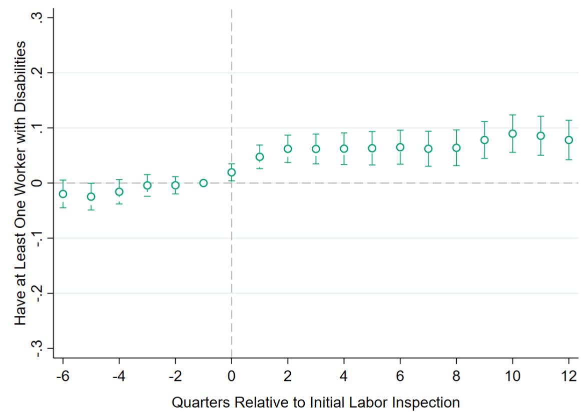


Note: Graph illustrates the geographic variation in interaction between measures of potential demand and enforcement capacity across local labor markets (micro regions) in Brazil. Potential demand is defined as the total number of jobs in the private sector to people with disabilities if there is perfect compliance with the AA quota in 1998, which are calculated from the distribution of firm size, divided by the total number of people with disabilities in 2000. Enforcement capacity is proxied by the minimum distance to the nearest labor office belonging to the same state within each micro region. Sources: 1998 RAIS, 2000 Demographic Census data, and labor offices' addresses.

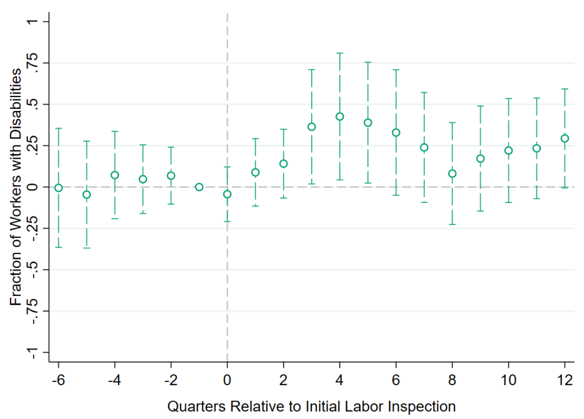
Figure 3: Effects of AA Quota on Employment



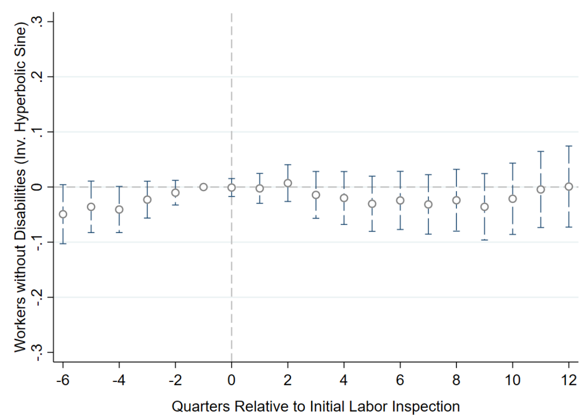
(a) Workers with Disabilities (Inverse Hyperbolic Sine)



(b) Have at Least One Worker with Disabilities



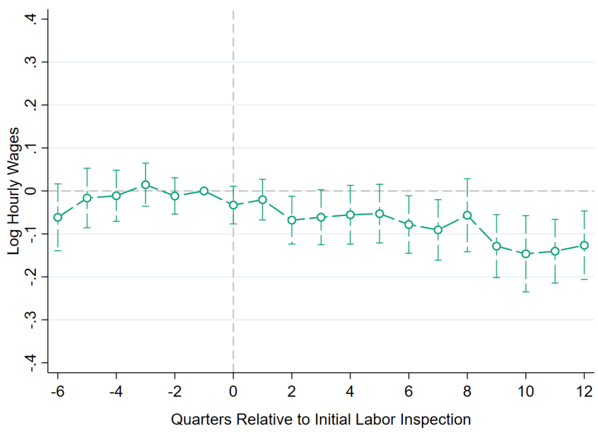
(c) Share of Workers of with Disabilities



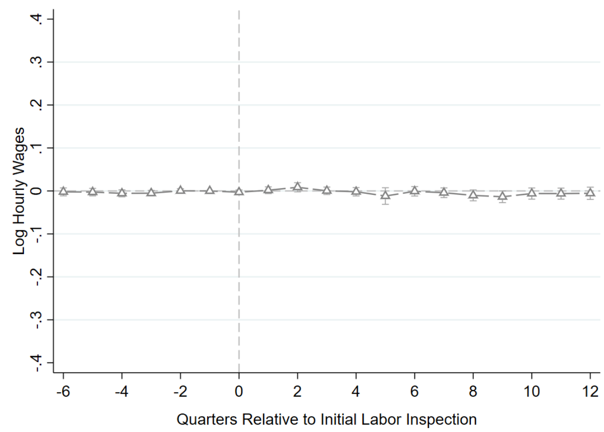
(d) Workers without Disabilities (Inverse Hyperbolic Sine)

Note: This figure reports point estimates of the quarterly effects of the AA quota on employment considering the intensive margin (inverse hyperbolic sine transformation of workers with disabilities), the extensive margin (indicator for having at least one worker with disabilities), the share of workers with disabilities (defined as total workers with disabilities divided by the total number of workers), and total workers without disabilities (its inverse hyperbolic sine transformation) as outcome variables. The omitted category is the quarter before inspection. More details can be found in Table 3.

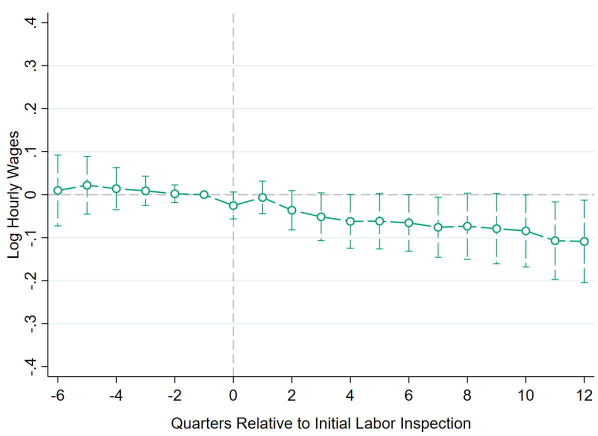
Figure 4: Effects of AA Quota on Wages



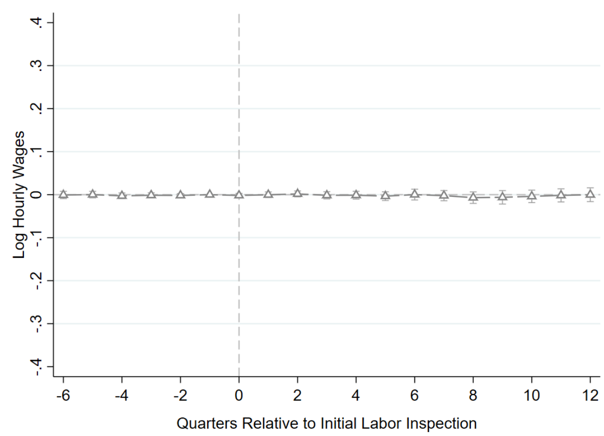
(a) Workers with Disabilities



(b) Workers without Disabilities



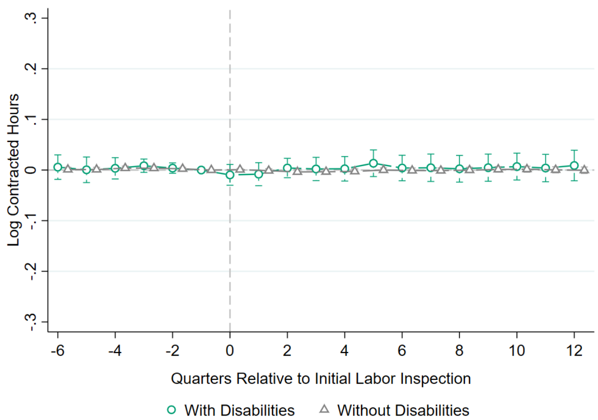
(c) Incumbent Workers with Disabilities



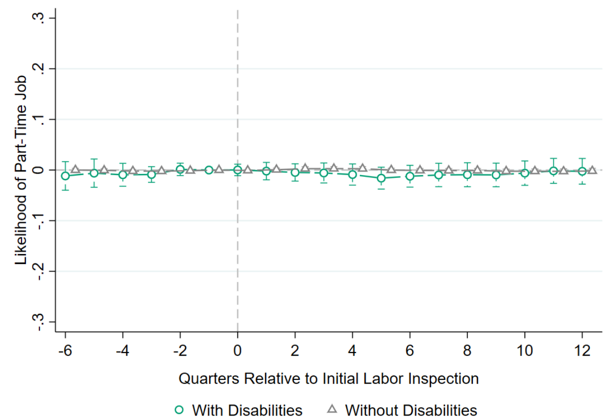
(d) Incumbent Workers without Disabilities

Note: This figure reports point estimates of the quarterly effects of the AA quota on log hourly wages. I consider separately workers with and without disabilities. Figures 4(c) and 4(d) refer to incumbent workers with and without disabilities. The omitted category is the quarter before inspection. More details can be found in Table 5.

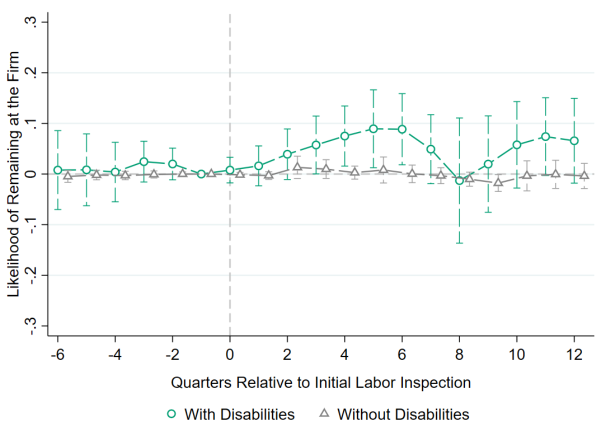
Figure 5: Effects of AA Quota on Other Workers' Outcomes



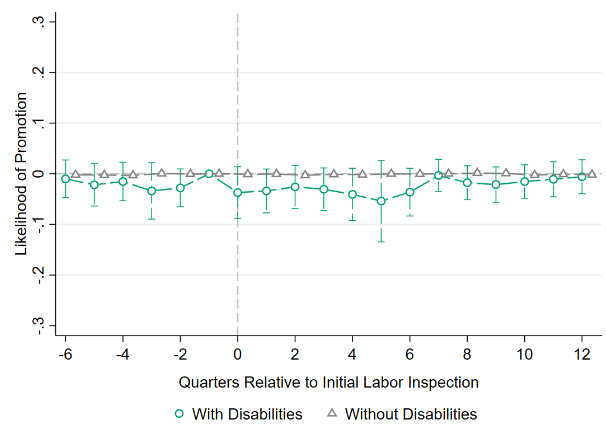
(a) Log Number of Hours



(b) Part-Time Employment



(c) Turnover



(d) Promotion

Note: This figure reports point estimates of the quarterly effects of the AA quota on log number of contracted hours, likelihood of part-time employment, likelihood of staying at the firm, and likelihood of promotion for workers with and without disabilities. The omitted category is the quarter before inspection. More details can be found in Table 6.

Table 1: Aggregate Analysis: Impacts on Employment

	(1)	(2)	(3)	(4)
	With Disabilities		Without Disabilities	
	Formal Employment	Informal Employment	Formal Employment	Informal Employment
(Strong Demand & Strong Enforcement) × Reform	0.011***	-0.006	0.007	0.002
	(0.003)	(0.003)	(0.004)	(0.004)
(Strong Demand & Weak Enforcement) × Reform	0.003	-0.007	0.004	0.003
	(0.005)	(0.005)	(0.004)	(0.003)
(Weak Demand & Strong Enforcement) × Reform	0.003	-0.006	0.003	-0.003
	(0.003)	(0.004)	(0.003)	(0.004)
Sample Size	1,018	1,018	1,018	1,018
Mean Dep. Var (in 2000)	0.116	0.146	0.191	0.204
Mean Dep. Var	0.143	0.142	0.230	0.182

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the aggregate effects of the reform on formal and informal employment rates for people with (Columns (1) and (2)) and without disabilities (Columns (3) and (4)). All columns refer to Equation (2). Means of dependent variables are computed from all micro regions in 2000. Standard errors are clustered at the state level.

Table 2: Aggregate Analysis: Impacts on Earnings

	(1)	(2)	(3)	(4)
	With Disabilities		Without Disabilities	
	Work Income	Non-Work Income	Work Income	Non-Work Income
(Strong Demand & Strong Enforcement) × Reform	34.55***	-2.08	18.37	-1.60
	(10.71)	(4.60)	(11.79)	(2.85)
(Strong Demand & Weak Enforcement) × Reform	18.16	-2.74	9.67	-2.35
	(23.42)	(6.59)	(10.29)	(3.23)
(Weak Demand & Strong Enforcement) × Reform	-4.08	4.19	6.04	-4.67
	(9.32)	(5.38)	(7.50)	(2.98)
Sample Size	1,018	1,018	1,018	1,018
Mean Dep. Var (in 2000)	363.78	125.33	641.41	74.22
Mean Dep. Var	398.64	149.07	691.32	85.47

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the aggregate effects of the reform on earnings, measured as work and non-work income, for people with (Columns (1) and (2)) and without disabilities (Columns (3) and (4)). All columns refer to Equation (2). Means of dependent variables are computed from all micro regions in 2000. Standard errors are clustered at the state level.

Table 3: Effects of AA Quota on Employment Outcomes

	(1) (IHS) Workers with Disabilities	(2) Have at Least One Worker with Disabilities	(3) Share of Workers with Disabilities	(4) (IHS) Workers without Disabilities
Panel A: Dynamic Impacts				
Immediate ($k = 0$)	0.025**	0.019**	-0.044	-0.001
	(0.010)	(0.008)	(0.084)	(0.008)
Short Run ($k = 6$)	0.113***	0.065***	0.329*	-0.024
	(0.024)	(0.016)	(0.193)	(0.027)
Long Run ($k = 12$)	0.157***	0.078***	0.294*	0.001
	(0.028)	(0.018)	(0.153)	(0.037)
Panel B: Aggregate Impacts				
Post $\times$ Quota	0.124***	0.077***	0.192*	0.018
	(0.018)	(0.012)	(0.115)	(0.026)
Sample Size	60,000	60,000	60,000	60,000
Firm and Year FEs	✓	✓	✓	✓
State and Industry Trends	✓	✓	✓	✓
# Firms	3,000	3,000	3,000	3,000
Mean Dep. Var (Control)	0.104	0.084	0.394	4.869

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the firm-level effects of the AA quota on several employment outcomes: inverse hyperbolic sine transformation (IHS) of total number of workers with disabilities, indicator for having at least one worker with disabilities, share of workers with disabilities relative to total number of workers, and IHS of total number of workers without disabilities. All columns refer to Equation (4). Means of dependent variables are computed from the control group in the quarterly window [-6, -1] before inspection. Standard errors are clustered at the firm level.

Table 4: Effects of AA Quota on Firm Outcomes

	(1) (IHS) Average Wages	(2) Average Wages	(3) Exit
Panel A: Dynamic Impacts			
Immediate ($k = 0$)	-0.0002	1.5002	0.0001
	(0.0045)	(13.155)	(0.0004)
Short Run ($k = 6$)	-0.0151	16.264	-0.0117
	(0.0161)	(20.801)	(0.0086)
Long Run ($k = 12$)	-0.0517	9,012	-0.0058
	(0.0333)	(24.928)	(0.0116)
Panel B: Aggregate Impacts			
Post × Quota	-0.009	14.227	-0.008
	(0.011)	(11.690)	(0.006)
Sample Size	60, 000	60,000	70,300
Firm and Year FEs	✓	✓	✓
State and Industry Trends	✓	✓	✓
Mean Dep. Var (Control)	7.434	1,016.30	0

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the firm-level effects of the AA quota on several firm outcomes: inverse hyperbolic sine transformation (IHS) of average wages of workers without disabilities, average wages of workers without disabilities, and firm exit. All columns refer to Equation (4). Means of dependent variables are computed from the control group in the quarterly window [-6, -1] before inspection. Standard errors are clustered at the firm level.

Table 5: Effects of AA Quota on Wages

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dynamic Impacts (Disabled) (N = 33,897)						
Immediate ($k = 0$)	-0.023	-0.032	-0.029	-0.033	-0.025	0132
	(0.023)	(0.023)	(0.023)	(0.022)	(0.016)	(0.139)
Short Run ($k = 6$)	-0.097***	-0.076**	-0.094***	-0.078**	-0.066**	0.064
	(0.038)	(0.034)	(0.037)	(0.034)	(0.034)	(0.120)
Long Run ($k = 12$)	-0.123***	-0.125***	-0.128***	-0.126***	-0.109***	-0.031
	(0.043)	(0.042)	(0.042)	(0.041)	(0.049)	(0.104)
Panel B: Aggregate Impacts (Disabled) (N = 33,897)						
Post × Quota	-0.062**	-0.048*	-0.062**	-0.061**	-0.056*	0.002
	(0.029)	(0.029)	(0.029)	(0.029)	(0.032)	(0.074)
Panel C: Dynamic Impacts (Non-Disabled) (N = 7,247,768)						
Immediate ($k = 0$)	-0.002	-0.003	-0.002	-0.002	-0.002	0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.009)
Short Run ($k = 6$)	0.002	0.001	-0.001	0.002	0.001	-0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.012)
Long Run ($k = 12$)	-0.007	-0.006	-0.007	-0.007	-0.000	-0.013
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.016)
Panel D: Aggregate Impacts (Non-Disabled) (N = 7,247,768)						
Post × Quota	-0.002	0.000	0.002	-0.001	-0.001	-0.006
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
Firm and Quarter FEs	✓	✓	✓	✓	✓	✓
State and Industry Trends	✓	✓	✓	✓	✓	✓
Individual Controls		✓		✓		✓
Occupation FE			✓	✓		✓
Worker FE					✓	
Sample						New Hires

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the worker-level effects of the AA quota on log hourly wages for workers with (Panels A and B) and without (Panels C and D) disabilities. Panels A and C refer to event-study difference-in-differences from Equation (5), while Panels B and D report aggregate difference-in-differences estimates from Equation (6). Column (1) refers to a model with firm and quarter fixed effects and state and industry trends. Column (2) adds individual controls (gender, race, educational level fixed effects, age, and square age). Column (3) includes occupation fixed effects. Column (4) refers to the preferred specification described in Equation (6). Column (5) includes worker, firm and quarter fixed effects, along with state and industry trends. Column (6) has the same specification as Column (4) with the sample restricted to new hires. Standard errors are clustered at the firm level.

Table 6: Effects of AA Quota on Workers' Outcomes

	(1) Log Hours	(2) Part-Time	(3) Turnover	(4) Promotion
Panel A: Dynamic Impacts (Disabled) (N = 33,897)				
Immediate ($k = 0$)	-0.010	0.000	0.008	-0.037
	(0.010)	(0.006)	(0.013)	(0.026)
Short Run ($k = 6$)	0.004	-0.012	0.089**	-0.036
	(0.013)	(0.011)	(0.036)	(0.024)
Long Run ($k = 12$)	0.009	-0.003	0.066	-0.006
	(0.015)	(0.013)	(0.043)	(0.018)
Panel B: Aggregate Impacts (Disabled) (N = 33,897)				
Post × Quota	-0.001	-0.001	0.038	-0.014*
	(0.012)	(0.011)	(0.026)	(0.008)
Panel C: Dynamic Impacts (Non-Disabled) (N = 7,247,768)				
Immediate ($k = 0$)	0.001	-0.001	-0.002	-0.008
	(0.001)	(0.001)	(0.002)	(0.002)
Short Run ($k = 6$)	-0.001	-0.001	0.000	-0.001
	(0.003)	(0.002)	(0.009)	(0.002)
Long Run ($k = 12$)	-0.000	-0.002	-0.004	-0.002
	(0.003)	(0.003)	(0.127)	(0.002)
Panel D: Aggregate Impacts (Non-Disabled) (N = 7,247,768)				
Post × Quota	-0.002	0.004	0.001	0.000
	(0.002)	(0.002)	(0.006)	(0.000)
Firm and Quarter FEs	✓	✓	✓	✓
State and Industry Trends	✓	✓	✓	✓
Individual Controls	✓	✓		✓
Occupation FE	✓	✓		✓
Worker FE			✓	

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the worker-level effects of the AA quota on log contracted hours, likelihood of having a part-time job, likelihood of staying at the firm, and likelihood of promotion. Results are reported for workers with (Panels A and B) and without disabilities (Panels C and D) separately. Panels A and C refer to the preferred specification described in Equation (6), whereas Panels B and D refer to Equation (5). The only exception is Column (3): the specification for the likelihood of staying at the firm considers worker, firm and quarter fixed effects and state- and industry-specific trends. Standard errors are clustered at the firm level.

Table 7: Heterogeneity: Effects of AA Quota on Wages

	(1)	(2)	(3)	(4)
	Educational Level		**On-the-Job Interactions**	
Post × Quota	-0.073*	-0.031	-0.090*	-0.048
	(0.039)	(0.075)	(0.049)	(0.045)
Sample Size	31,177	2,721	15,230	17,958
Sample Restriction	No College	College	Weak Interactions	Strong Interactions
Firm and Quarter FEs	✓	✓	✓	✓
State and Industry Trends	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the heterogeneous effects of the AA quota on log hourly wages for workers with disabilities. Columns (1) and (2) restrict the samples to workers without and with a college degree. Columns (3) and (4) refer to samples of workers with weak and strong interactions with co-workers, classified as below and above the median of communicating with supervisors and peers. This measure comes from occupations "providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person" as listed in the O*NET database. All columns refer to the preferred specification described in Equation (6). Standard errors are clustered at the firm level.

Table 8: Discrete Choice Estimates

	(1)	(2)
$\hat{\beta}_0$	0.5544***	1.1726***
	(0.0459)	(0.0888)
$\hat{\beta}_1$	-0.0002***	-0.0006***
	(0.0000)	(0.0000)
$M\hat{R}PL_d$	2,338.063	2,044.769
	(204.40)	(113.48)
Mean Wages	1,854.74	1,854.74
$M\hat{R}PL_d/\bar{w}$	1.2606	1.1025
[Lower Bound; Upper Bound]	[1.0446; 1.4766]	[0.9825; 1.2224]
Model	Probit	Logit

Note: This table reports the point estimates after estimating Equation (13) via maximum likelihood using normal (Column (1)) and logistic (Column (2)) distributions. $M\hat{R}PL_d/\bar{w}$ is defined as the ratio between firms' estimated monthly marginal revenue product of labor and average wages. Lower and upper bounds for the ratio account for 95-percent confidence intervals. Standard errors are bootstrapped.

A Institutional Context and Data

A.1 Tables and Figures

Table A1: Disability Gaps in the Labor Market

	(1) Economically Active	(2) Worked	(3) Informal Employment	(4) (IHS) Work Income
Severe Difficulty	-0.182***	-0.057***	0.034***	-0.195***
	(0.008)	(0.003)	(0.002)	(0.010)
Some Difficulty	-0.026***	-0.022***	0.018***	-0.099***
	(0.003)	(0.001)	(0.001)	(0.006)
Sample Size	6,40,6401	4,752,620	4,372,587	4,372,587
Sample Restriction	-	Econ. Active	Worked	Worked
Mean (Without Disabilities)	0.794	0.936	0.180	7.458
Mean (Severe Difficulty)	0.567	0.855	0.250	7.070
Mean (Some Difficulty)	0.740	0.901	0.215	7.276
Individual Controls	✓	✓	✓	✓
Occup. & Sector Controls		✓	✓	✓

Note: This table displays gaps in labor market outcomes across disabilities using the 2010 Census. The samples include working-age individuals aged 25 to 54. I create indicator variables for whether individuals report having severe and some difficulties in one or more of the following activities: seeing, hearing, walking or climbing stairs. I regress labor market outcomes on having severe and some difficulties. The omitted disability group is no disabilities (no difficulties). All specifications include potential experience, potential experience squared, dummies for educational categories and rural areas, and municipality fixed effects. Columns (2) to (4) additionally include occupation and economic sector fixed effects. The dependent variables are indicators for economically active individuals, having worked in the last week of July of 2010 and employment in the informal sector, and the inverse hyperbolic sine transformation of work income. In Column (2), the sample is further restricted to economically active individuals. In Columns (3) and (4), the sample refers to individuals who have worked in the last week of July of 2010. Means of dependent variables across disability groups are reported. Standard errors are clustered at the state level.

A.2 List of Disabilities

As previously explained in Section 2.2, the Anti-Discrimination Act (Article 4) outlines a list of disabilities that qualify for reserved jobs from the AA quota regulation. Throughout the years, this list has been modified to include other disabilities to accommodate decisions made by the Ministry of Labor, Labor Courthouses (*Justiça do Trabalho*), and Supreme Courts. The list of disabilities include:

Physical. Complete or partial alteration of one or more segments of the human body, causing impairment of physical function. It can be paraplegia, paraparesis, monoplegia, monoparesis, tetraplegia, tetraparesis, triplegia, triparesia, hemiplegia, hemiparesis, ostomy, amputation or absence of a limb, cerebral palsy, dwarfism, limbs with congenital or acquired deformity, except for aesthetic deformities and those that do not lead to difficulties. People with reduced mobility also qualify for AA quota.

Hearing. Bilateral (partial or total) loss of 41 decibels (dB) or more, measured by an audiogram test at frequencies of 500HZ, 1000HZ, 2000Hz, and 3000Hz. It is equivalent to moderate to profound hearing loss.

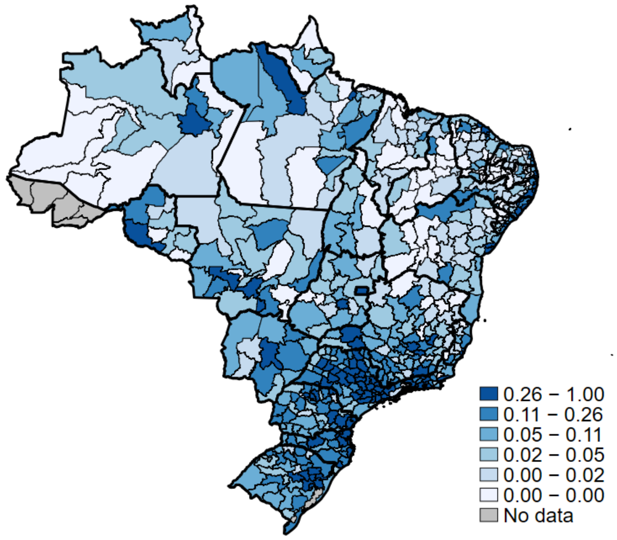
Visual. blindness (visual acuity equal to or less than 0.05 in the best eye with the best optical correction); low vision (visual acuity between 0.3 and 0.05 in the best eye with the best optical correction); cases in which the sum of the visual field measured in both eyes is equal to or less than 60 degrees; simultaneous occurrence of any of the previous conditions; and monocular vision (visual acuity equal to or less than 0.05 in one eye with the best optical correction). Monocular vision was added to the list in 2011 (CONJUR/MTE 444/11).

Cognitive and Mental Disorders. Permanent cognitive or mental disorders that create limitations in two or more of the following skills: communication, personal care, social skills, use of community resources, health and safety, academic skills, leisure, and work. Examples include learning disabilities (e.g., dyscalculia) and autism spectrum disorder. The latter was added to the list in 2012 (Law 12,764).

Multiple. Multiple disabilities encompass two or more disabilities.

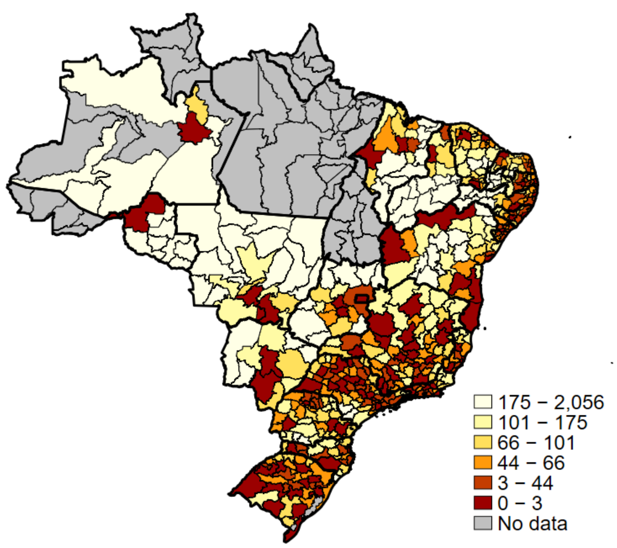
B Figures (Aggregate Analysis)

Figure B1: Cross-Market Variation: Potential Demand



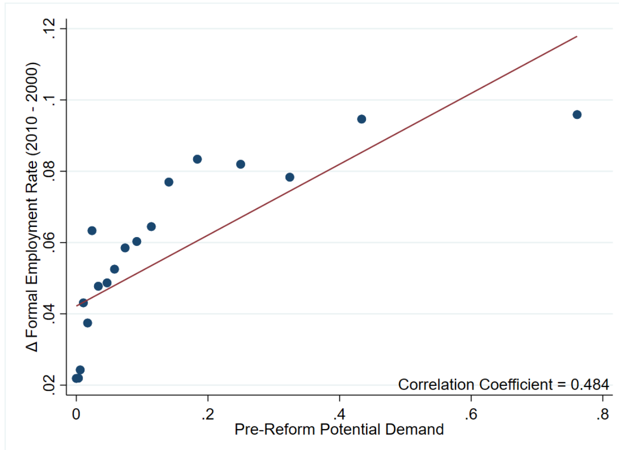
Note: Graph illustrates the geographic variation in potential demand measure across local labor markets (micro regions) in Brazil. Potential demand is defined as the total number of jobs in the private sector that would be available due to the hiring quota regulation in 1998, which is calculated from the distribution of firm size, divided by the total number of people with disabilities in 2000. Sources: 1998 RAIS and 2000 Demographic Census data.

Figure B2: Cross-Market Variation: Enforcement Capacity



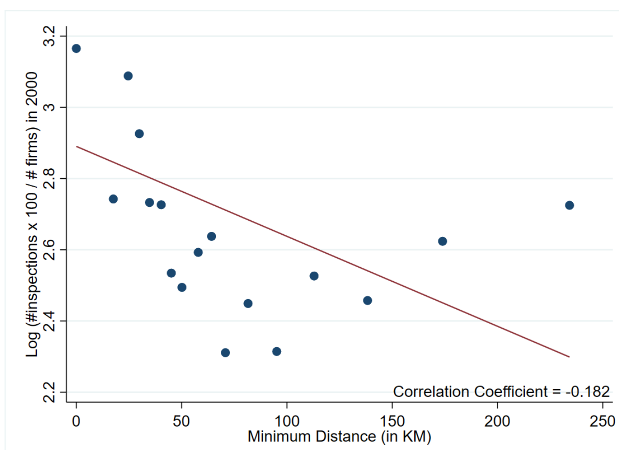
Note: Graph illustrates the geographic variation in enforcement capacity across local labor markets (micro regions) in Brazil. Enforcement capacity is computed by obtaining the driving distance between the centroid of each municipality and the nearest labor office created prior to 2000s. I then define the minimum distance of the municipalities that belong to each micro region as the minimum distance between each micro region and the nearest labor office. Sources: data on labor offices from the Ministry of Labor and Ponczek and Ulyssea (2021).

Figure B3: Pre-Reform Potential Demand and Actual Employment Rate



Note: This binned scatter plot shows the relationship between the pre-reform potential demand and the increase in employment rate in the formal sector for people with disabilities between 2000 and 2010. The former is defined as the total number of jobs in the private sector that would be available due to the hiring quota regulation in 1998, which is calculated from the distribution of firm size, divided by the total number of people with disabilities in 2000. The latter is defined as the share of formal employment in 2010 relative to 2000. The unit of observation is a micro region. The right hand side variable is grouped into 20 bins. The correlation coefficient is 0.484. Sources: 1998 RAIS and 2000 and 2010 Demographic Census data.

Figure B4: Pre-Reform Driving Distance to Labor Offices and Frequency of Inspections



Note: Graph illustrates the relationship between distance to labor offices and the number of inspections per firm. Sources: data on labor offices, This binned scatter plot shows the relationship between the pre-reform distance to the nearest labor office and the frequency of labor inspections in 2000. The former is defined as the minimum driving distance between each micro region and the nearest labor office. The latter is defined as log of total number of inspections normalized by the number of firms in each micro region in 2000. The unit of observation is a micro region. The right hand side variable is grouped into 20 bins. The correlation coefficient is -0.182. Sources: data on labor offices from the Ministry of Labor and Ponczek and Ulyssea (2021), and data on labor inspections.

Figure B5: Impact of Reform on Formal Employment of People with Disabilities Using RAIS

Note:. This figure reports point estimates of the annual effects of reform on share of formal employment of people with disabilities using both the RAIS and Census data. The omitted category is micro regions with weak enforcement and weak demand in 2000.

C Tables (Aggregate Analysis)

Table C1: Descriptive Statistics at the Micro Region Level

	(1) Mean	(2) SD
Panel A: People Without Disabilities		
Formal Employment	0.191	0.099
Informal Employment	0.204	0.048
Work Income (in BRL *reais*)	641.41	318.40
Non-Work Income (in BRL *reais*)	74.22	41.28
Panel B: People With Disabilities		
Formal Employment	0.116	0.065
Informal Employment	0.146	0.041
Work Income (in BRL *reais*)	363.78	211.90
Non-Work Income (in BRL *reais*)	125.32	57.65
Panel C: Demographic and Economic Variables		
Share Female	0.498	0.012
Share College Educated	0.035	0.028
Share Urban	0.679	0.180
Unemployment Rate	0.111	0.039
Income *per capita* (in BRL *reais*)	397.16	211.05
Population	36,334.07	81,152.06
Number of Micro Regions	509	

Note: This table reports descriptive statistics (mean and standard deviation) in 2000 at the micro region level. Shares of formal and informal employment, average work and non-work incomes, shares of female, college educated, and urban population, unemployment rate, average income per capita, and average population are computed using individual-level data and sampling weights from the 2000 Census data.

Table C2: Aggregate Analysis: Impacts on Formal and Informal Work Income

	(1)	(2)	(3)	(4)
	With Disabilities		Without Disabilities	
	Formal	Informal	Formal	Informal
(Strong Demand & Strong Enforcement) × Reform	11.462***	-4.744	9.442	-2.525
	(4.035)	(3.245)	(7.006)	(2.087)
(Strong Demand & Weak Enforcement) × Reform	10.322	-4.101	14.305**	0.628
	(7.923)	(2.862)	(6.444)	(1.924)
(Weak Demand & Strong Enforcement) × Reform	0.233	-3.641	5.194	-3.636*
	(3.524)	(2.725)	(5.087)	(1.752)
Sample Size	1,018	1,018	1,018	1,018
Control Mean (in 2000)	102.53	43.96	192.71	72.42
Control Mean	134.17	50.32	246.48	78.06

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the aggregate effects of reform on formal and informal work income for people with (Columns (1) and (2)) and without disabilities (Columns (3) and (4)). All columns refer to Equation (2). Means of dependent variables are computed from all micro regions in 2000. Standard errors are clustered at the state level.

Table C3: Alternative Exposure Definitions

	(1) Formal Employment	(2) Formal Employment	(3) Work Income	(4) Work Income
Panel A: Mean				
(Strong Demand & Strong Enforcement) × Reform	0.012***	0.006	32.284**	12.522
	(0.004)	(0.005)	(12.193)	(12.154)
(Strong Demand & Weak Enforcement) × Reform	0.002	0.004	25.941	9.682
	(0.004)	(0.004)	(21.884)	(9.784)
(Weak Demand & Strong Enforcement) × Reform	0.003	0.002	3.433	-2.684
	(0.003)	(0.003)	(10.685)	(6.883)
Panel B: Maximum				
(Strong Demand & Strong Enforcement) × Reform	0.013***	0.007	31.731**	19.364
	(0.004)	(0.005)	(15.107)	(11.617)
(Strong Demand & Weak Enforcement) × Reform	0.004	0.003	31.845	7.874
	(0.004)	(0.004)	(19.492)	(10.018)
(Weak Demand & Strong Enforcement) × Reform	0.005*	0.002	9.486	3.590
	(0.003)	(0.003)	(11.046)	(7.636)
Sample Size	1,018	1,018	1,018	1,018
Sample Restriction	Disabled	Non-Disabled	Disabled	Non-Disabled
Control Mean (in 2000)	0.116	0.191	363.76	641.41
Control Mean	0.143	0.229	398.64	691.32

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the aggregate effects of reform on employment and work income using alternative definitions of exposure measure. In Panel A, I use the mean, rather than the minimum, of distances from all municipalities that belong to each micro region to define enforcement capacity. Panel B considers the maximum of distances. Columns (1) and (3) restrict the sample to people with disabilities, while Columns (2) and (4) refer to people without disabilities. All columns refer to Equation (2). Means of dependent variables are computed from all micro regions in 2000. Standard errors are clustered at the state level.

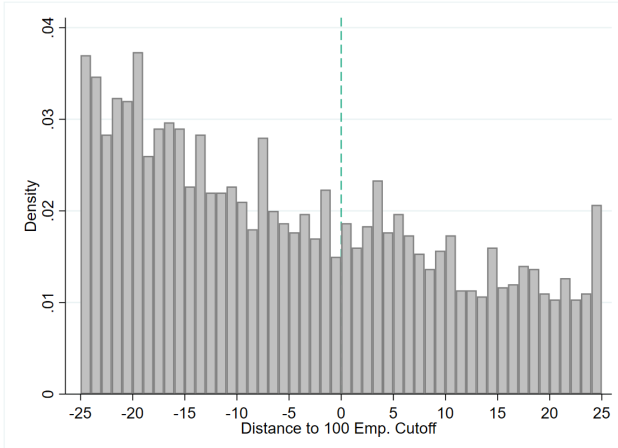
Table C4: Impacts on Migration and Welfare Program Take-Up

	(1) Migration	(2) Welfare Program
Strong Demand & Strong Enforcement) × Reform	0.016	-0.025***
	(0.016)	(0.008)
(Strong Demand & Weak Enforcement) × Reform	0.022	-0.018**
	(0.013)	(0.007)
(Weak Demand & Strong Enforcement) × Reform	0.011	-0.003
	(0.018)	(0.006)
Sample Size	1,018	1,018
Sample Restriction	Disabled	Disabled
Control Mean (in 2000)	0.297	0.260
Control Mean	0.265	0.311

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the aggregate effects of reform on migration rate and likelihood of receiving a welfare program for people with disabilities. Migration is defined as having moved to another state in the last five years. All columns refer to Equation (2). Means of dependent variables are computed from all micro regions in 2000. Standard errors are clustered at the state level.

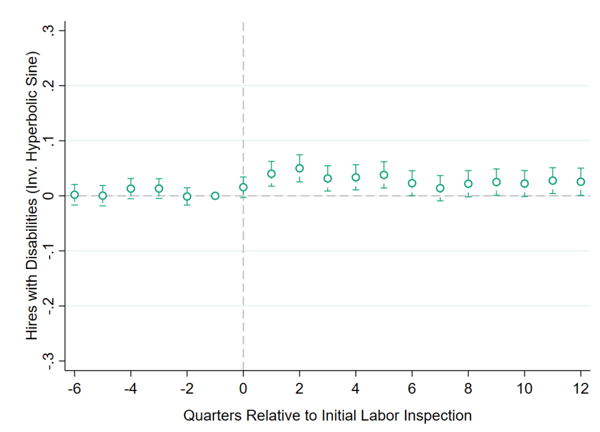
D Figures (Firm-Level Analysis)

Figure D1: Histogram

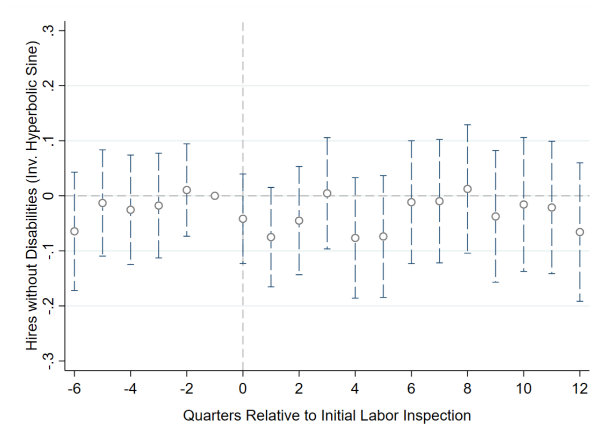


Note: Histogram depicts the distribution of firm size, measured by total number of employees, relative to the affirmative action quota cutoff of 100 employees within one point bins. Further details about the sample can be found in Table E1. Sources: RAIS and data on inspections.

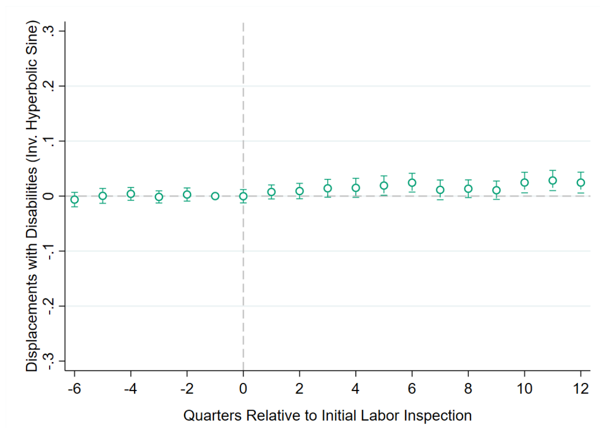
Figure D2: Additional Effects of AA Quota on New Hires and Separations



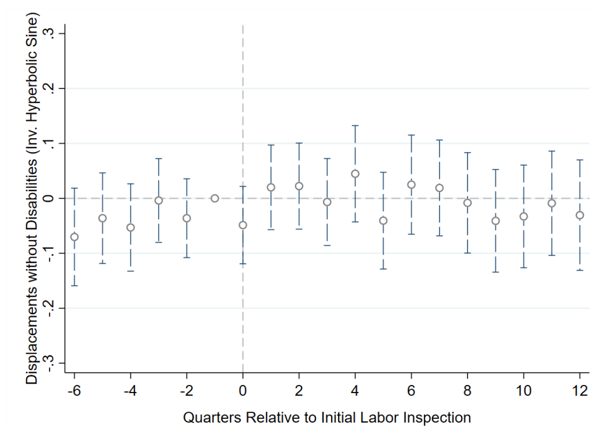
(a) (IHS) Hires with Disabilities



(b) (IHS) Hires without Disabilities



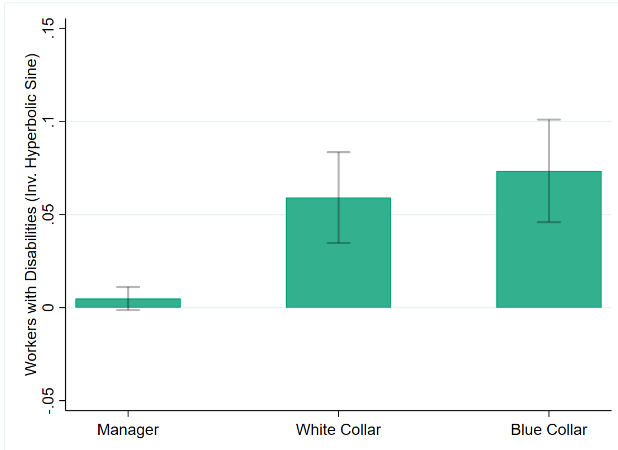
(c) (IHS) Displaced with Disabilities



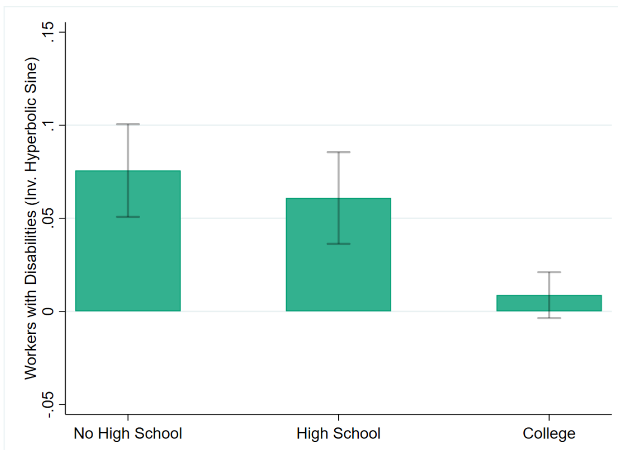
(d) (IHS) Displaced without Disabilities

Note: This figure reports point estimates of the quarterly effects of AA quota on hires and separations of workers with and without disabilities. The outcome variables are the inverse hyperbolic sine transformation of these variables. The omitted category is the quarter before inspection. All graphs refer to Equation (4).

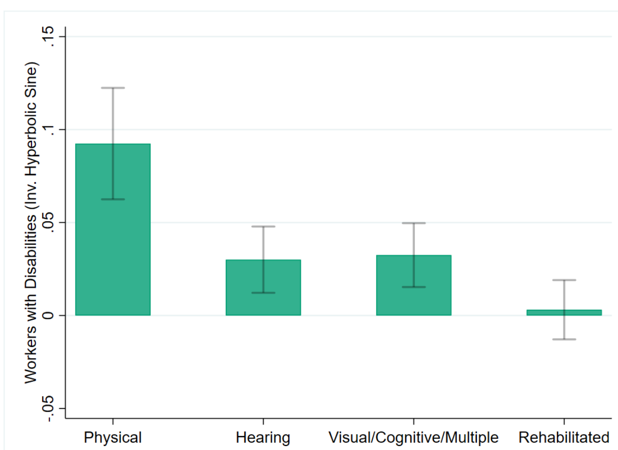
Figure D3: Heterogeneous Employment Effects of AA Quota



(a) Occupations (DiD)



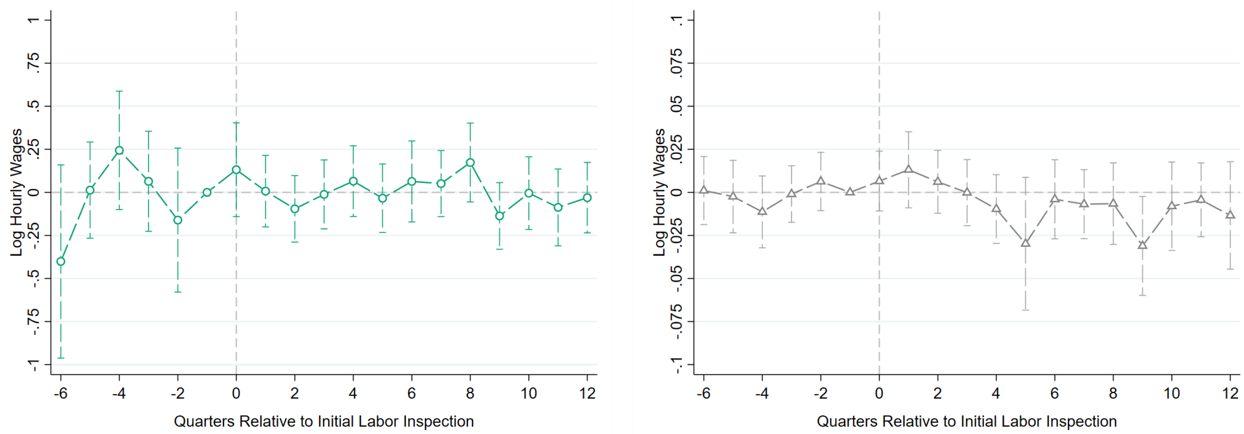
(b) Educational Levels (DiD)



(c) Disabilities (DiD)

Note: This figure reports aggregate point estimates of the effects of AA quota on employment of people with disabilities considering heterogeneity across occupations, educational levels, and disabilities. The omitted category is the quarter before inspection. More details can be found in Tables E2–E4, Appendix E.

Figure D4: Effects of AA Quota on Wages (New Hires)

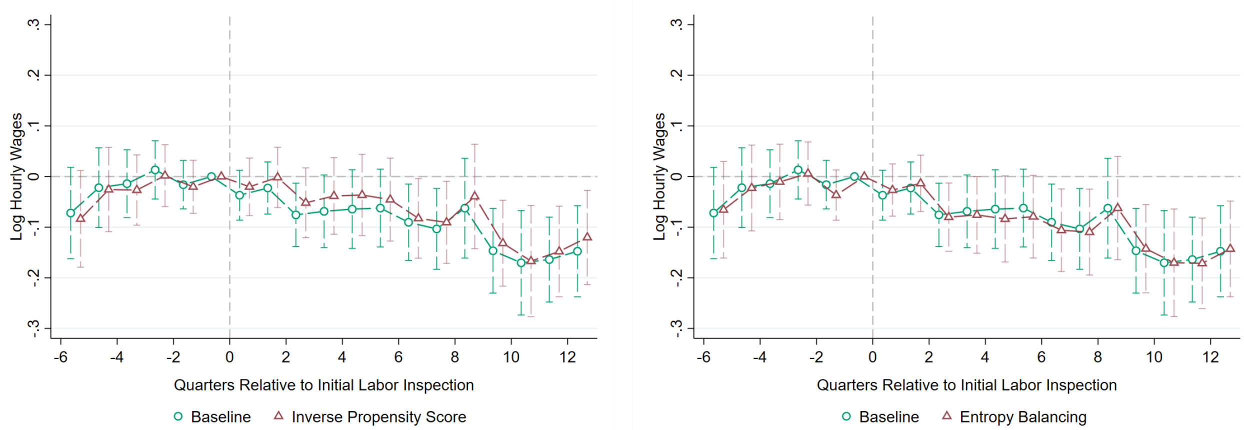


(a) New Hires with Disabilities

(b) New Hires without Disabilities

Note: This figure reports point estimates of the quarterly effects of AA quota on log hourly wages for new hires with and without disabilities separately. The omitted category is the quarter before inspection. More details can be found in Column (6) of Table 5.

Figure D5: Robustness of Wage Effects: Re-Weighting Methods



(a) Inverse Propensity Score Weights

(b) Entropy-Balancing Weights

Note: This figure reports point estimates of the quarterly effects of AA quota on log hourly wages for workers with disabilities using re-weighting methods. The green estimates repeat the baseline specification from Column (4) of Table 5. Figure 5(a) displays coefficients using inverse propensity score weights from the following pre-inspection characteristics: gender, race, age, squared age, education, and occupation. Figure 5(a) shows coefficients using entropy-balancing weights from Hainmueller (2012).

E Tables (Firm-Level Analysis)

Table E1: Descriptive Statistics: Firm-Level Sample

	(1)		(2)		(3)		(4)	
	Control Firms				Treated Firms			
	Before		After		Before		After	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Main Variables								
# Employees without Disabilities	72.23	25.43	97.24	81.45	93.29	37.28	131.21	275.60
# Employees with Disabilities	0.31	3.69	0.48	4.35	0.29	2.69	0.74	4.33
IHS Employees without Disabilities	4.87	0.58	5.09	0.68	5.11	0.62	5.35	0.72
IHS Employees with Disabilities	0.10	0.42	0.19	0.55	0.14	0.44	0.35	0.68
Has at Least One Employee with Disabilities	0.08	0.28	0.14	0.34	0.12	0.33	0.25	0.43
Share Employees with Disabilities (x100)	0.39	4.53	0.44	3.95	0.31	2.91	0.57	3.74
IHS Hires without Disabilities	2.81	1.08	2.60	1.39	3.09	1.10	2.87	1.46
IHS Hires with Disabilities	0.02	0.18	0.03	0.24	0.02	0.16	0.06	0.28
IHS Displaced without Disabilities	2.01	0.96	2.46	0.96	2.24	1.03	2.73	0.99
IHS Displaced with Disabilities	0.01	0.14	0.02	0.16	0.01	0.12	0.04	0.21
Log Average Earnings	7.37	0.51	7.44	0.60	7.38	0.53	7.44	0.71
Location								
Central West Region	0.07	0.25	0.07	0.26	0.05	0.22	0.05	0.22
North Region	0.04	0.20	0.04	0.20	0.04	0.20	0.04	0.20
Northeast Region	0.10	0.31	0.10	0.31	0.11	0.31	0.11	0.32
South Region	0.22	0.41	0.22	0.41	0.26	0.44	0.25	0.44
Southeast Region	0.56	0.50	0.56	0.50	0.54	0.50	0.54	0.50
Sector								
Construction	0.06	0.25	0.07	0.25	0.08	0.27	0.08	0.27
Commerce	0.19	0.40	0.18	0.39	0.17	0.38	0.16	0.37
Transp., Storage & Commun.	0.09	0.28	0.09	0.29	0.08	0.27	0.08	0.27
Transformation Industry	0.30	0.46	0.30	0.46	0.29	0.45	0.29	0.46
Real Estate	0.15	0.36	0.15	0.36	0.16	0.37	0.15	0.36
Services	0.04	0.19	0.04	0.19	0.04	0.20	0.04	0.20
Other Categories	0.17	0.37	0.16	0.37	0.19	0.39	0.19	0.39
N	3,309		3,309		2,013		2,013	

Note: This table reports descriptive statistics for firms using information from RAIS data. The first two columns refer to a sample of control firms. Columns (3) and (4) report summary statistics for the treatment group. Further details on the sample construction are found in Section 5. Odd columns indicate summary statistics using the averages in the quarterly window [-6,-1] before labor inspection while even columns refer to the quarterly window [0, 12] following it. The variables are: total number of employees with and without disabilities, log number of employees with and without disabilities, indicator for having at least one employee with disabilities, share of employees with disabilities, log average earnings, indicator variables for whether the establishment is located in Central-West, North, Northeast, South and Southeast regions, average population of the municipality in which the establishment is located, and indicator variables for economic sector the establishment belongs to (administration, construction, commerce, transportation, storage and communication, transformation industry, services, or other sectors). Sources: RAIS and data on inspections.

Table E2: Heterogeneity in Employment Effects by Occupations

	(1) Manager	(2) Professional	(3) White Collar	(4) Blue Collar
Panel A: Dynamic Impacts				
Immediate ($k = 0$)	-0.000	0.003	0.011**	0.012
	(0.002)	(0.004)	(0.005)	(0.009)
Short Run ($k = 6$)	0.003	0.017*	0.052***	0.062***
	(0.005)	(0.009)	(0.015)	(0.019)
Long Run ($k = 12$)	0.003	0.026**	0.076***	0.089***
	(0.005)	(0.011)	(0.017)	(0.022)
Panel B: Aggregate Impacts				
Post × Quota	0.005	0.013*	0.053***	0.073***
	(0.003)	(0.007)	(0.011)	(0.014)
Sample Size	60,000	60,000	60,000	60,000
Firm and Year FEs	✓	✓	✓	✓
State and Industry Trends	✓	✓	✓	✓
# Firms	3,000	3,000	3,000	3,000
Mean Dep. Var (Control)	0.008	0.018	0.024	0.072

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports heterogeneous effects of AA quota across occupational groups: managerial, high-skill professional, low-skill white collar, and blue collar. All columns refer to Equation (4) and use the inverse hyperbolic sine transformation of number of workers with disabilities in occupational groups as main outcomes. Means of dependent variables are computed from the control group in the quarterly window [-6, -1] before inspection. Standard errors are clustered at the firm level.

Table E3: Heterogeneity in Employment Effects by Educational Levels

	(1) No High School	(2) High School	(3) College
Panel A: Dynamic Impacts			
Immediate ($k = 0$)	0.010	0.012*	0.007*
	(0.008)	(0.006)	(0.004)
Short Run ($k = 6$)	0.072***	0.052***	0.011
	(0.019)	(0.017)	(0.009)
Long Run ($k = 12$)	0.084***	0.099***	0.014
	(0.020)	(0.020)	(0.010)
Panel B: Aggregate Impacts			
Post $\times$ Quota	0.076***	0.061***	0.009
	(0.013)	(0.013)	(0.006)
Sample Size	60,000	60,000	60,000
Firm and Year FEs	✓	✓	✓
State and Industry Trends	✓	✓	✓
# Firms	3,000	3,000	3,000
Mean Dep. Var (Control)	0.062	0.045	0.013

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports heterogeneous effects of AA quota across educational levels: without high school degree, with high school degree, and with college degree. All columns refer to Equation (4) and use the inverse hyperbolic sine transformation of number of workers with disabilities in educational levels as main outcomes. Means of dependent variables are computed from the control group in the quarterly window [-6, -1] before inspection. Standard errors are clustered at the firm level.

Table E4: Heterogeneity in Employment by Disabilities

	(1) Physical	(2) Hearing	(3) Vis./Cogn./ Multi.	(4) Rehab.
Panel A: Dynamic Impacts				
Immediate ($k = 0$)	0.029***	-0.004	0.001	-0.007
	(0.008)	(0.005)	(0.004)	(0.007)
Short Run ($k = 6$)	0.085***	0.029**	0.021**	-0.003
	(0.019)	(0.012)	(0.011)	(0.011)
Long Run ($k = 12$)	0.116***	0.028**	0.055***	0.004
	(0.023)	(0.014)	(0.013)	(0.011)
Panel B: Aggregate Impacts				
Post × Quota	0.092***	0.030***	0.032***	0.003
	(0.015)	(0.009)	(0.009)	(0.008)
Sample Size	51,574	51,574	51,574	51,574
Firm and Year FEs	✓	✓	✓	✓
State and Industry Trends	✓	✓	✓	✓
# Firms	3,000	3,000	3,000	3,000
Mean Dep. Var (Control)	0.057	0.027	0.008	0.009

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports heterogeneous effects of AA quota across types of disabilities: physical, hearing, visual, intellectual or multiple, and rehabilitated individuals. All columns refer to Equation (4) and use the inverse hyperbolic sine transformation of number of workers with specific disabilities as main outcomes. Means of dependent variables are computed from the control group in the quarterly window [-6, -1] before inspection. Standard errors are clustered at the firm level.

Table E5: Robustness Checks: Firms-Level Results

	(1) (IHS) employm.	(2) employm. (level)	(3) log employm.	(4) (IHS) employm.	(5) employm. (level)	(6) employm. (non-disabled)	(7) (IHS) employm.	(8) (IHS) employm.	(9) (IHS) employm.	(10) (IHS) employm.
Panel A: Dynamic Impacts										
Immediate ($k = 0$)	0.025**	-0.043	0.019**	0.025**	-0.079	-0.003	0.014	0.004	0.039***	0.035***
	(0.010)	(0.087)	(0.008)	(0.010)	(0.203)	(0.009)	(0.014)	(0.017)	(0.011)	(0.014)
Short Run ($k = 6$)	0.113***	0.397*	0.088***	0.113***	0.484	0.038	0.100***	0.077**	0.141***	0.136***
	(0.024)	(0.209)	(0.019)	(0.024)	(0.378)	(0.056)	(0.032)	(0.039)	(0.028)	(0.033)
Long Run ($k = 12$)	0.157***	0.401**	0.121***	0.158***	0.441	0.031	0.128***	0.127***	0.170***	0.172***
	(0.028)	(0.164)	(0.022)	(0.028)	(0.389)	(0.073)	(0.037)	(0.046)	(0.032)	(0.037)
Panel B: Aggregate Impacts										
Post × Quota	0.124***	0.262**	0.095***	0.126***	0.463*	0.042	0.094***	0.063**	0.152***	0.151***
	(0.018)	(0.117)	(0.014)	(0.018)	(0.281)	(0.054)	(0.024)	(0.029)	(0.021)	(0.024)
Sample Size	60,000	60,000	60,000	60,000	60,000	60,000	34,140	23,420	47,680	36,580
Firm and Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State and Industry Trends	✓	✓	✓	×	×	×	✓	✓	✓	✓
Sample Restriction	75-125 emp.	75-125 emp.	75-125 emp.	75-125 emp.	75-125 emp.	75-125 emp.	85-115 emp.	90-110 emp.	exc. 5 emp.	exc. 10 emp.
Model	OLS	OLS	OLS	OLS	Poisson	Poisson	OLS	OLS	OLS	OLS
# Firms	3,000	3,000	3,000	3,000	3,000	3,000	1,707	1,171	2,384	1,829
Mean Dep. Var (Control)	0.104	0.311	0.082	0.104	0.311	72.27	0.118	0.137	0.097	0.089

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports several robustness checks for the firm-level analysis. Column (1) repeats Column (1) from Table 3. Columns (2) and (3) refer to number of employees with disabilities and its natural logarithm as the dependent variables. Column (4) excludes state- and industry-specific trends from the set of firm controls. Columns (5) and (6) estimate a conditional fixed-effect Poisson model using number of employees with and without disabilities as dependent variables. Columns (7) and (8) consider narrower windows around the cutoff. Columns (9) and (10) excludes firms very close to the cutoff. Means of dependent variables are computed from the control group in the quarterly window [-6, -1] before inspection. Standard errors are clustered at the firm level.

Table E6: Descriptive Statistics: Worker-Level Sample

	(1)		(2)		(3)		(4)	
	Control Workers				Treated Workers			
	Before		After		Before		After	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Main Variables								
Has Disability	0.004	0.06	0.005	0.07	0.003	0.05	0.006	0.08
Log Hourly Earnings	2.19	0.65	2.28	0.68	2.20	0.66	2.28	0.70
Hourly Earnings	11.34	26.39	12.74	28.26	11.46	22.71	12.68	24.06
Contracted Hours (Monthly)	185.43	23.77	184.77	24.14	184.49	24.18	184.05	24.67
Male	0.66	0.48	0.66	0.48	0.65	0.48	0.63	0.48
White	0.67	0.47	0.63	0.48	0.69	0.46	0.65	0.48
Has College Degree	0.10	0.30	0.10	0.30	0.10	0.31	0.11	0.31
Manager	0.03	0.18	0.03	0.17	0.03	0.17	0.03	0.17
Professional	0.14	0.35	0.14	0.35	0.16	0.36	0.16	0.37
Low-Skill White Collar	0.16	0.37	0.17	0.38	0.16	0.36	0.17	0.37
Blue Collar	0.66	0.47	0.65	0.48	0.66	0.47	0.64	0.48
Location								
Central West Region	0.07	0.25	0.07	0.25	0.04	0.21	0.05	0.22
North Region	0.04	0.19	0.05	0.21	0.04	0.19	0.04	0.21
Northeast Region	0.10	0.30	0.11	0.31	0.10	0.30	0.10	0.30
South Region	0.23	0.42	0.21	0.40	0.27	0.44	0.23	0.42
Southeast Region	0.56	0.50	0.57	0.49	0.55	0.50	0.57	0.49
Sector								
Construction	0.06	0.23	0.07	0.26	0.06	0.24	0.08	0.27
Commerce	0.19	0.39	0.18	0.39	0.17	0.37	0.16	0.36
Transp., Storage & Commun.	0.09	0.28	0.09	0.29	0.07	0.26	0.08	0.27
Transformation Industry	0.30	0.46	0.29	0.45	0.29	0.45	0.26	0.44
Real Estate	0.14	0.35	0.16	0.37	0.17	0.37	0.22	0.41
Services	0.04	0.20	0.04	0.20	0.04	0.21	0.04	0.20
Other Categories	0.17	0.38	0.16	0.37	0.20	0.40	0.17	0.38
N	825,152		825,152		633,831		633,831	

Note: This table reports descriptive statistics for workers using information from RAIS data. The first two columns refer to a sample of workers from control firms. Columns (3) and (4) report summary statistics for the treatment workers. Further details on the sample construction are found in Section 5. Odd columns indicate summary statistics using the averages in the quarterly window [-6,-1] before labor inspection while even columns refer to the quarterly window [0, 12] following it. The variables are: indicator for having a disability, log hourly wages, absolute hourly wages, monthly number of hours contracted, indicators for male, white, having a college degree, indicators for manager, professional, low-skill white collar, and blue collar positions, indicator variables for whether the establishment is located in Central-West, North, Northeast, South and Southeast regions, average population of the municipality in which the establishment is located, and indicator variables for economic sector the establishment belongs to (administration, construction, commerce, transportation, storage and communication, transformation industry, services, or other sectors).

F Survey Data

F.1 Survey Overview

The pilot survey was implemented in collaboration with Oppen Social. The survey instrument included questions about affirmative action support, along with questions on challenges and concerns in hiring people with disabilities. The sample from the pilot survey has 60 firms from the RAIS data, with 31 firms having more than 100 employees.[44] In June of 2022, the Oppen Social reached out, within a window of seven days, to representatives of Human Resources (HR) departments from 764 and 751 firms found in the RAIS data with less and more than 100 employees. In cases in which the firm did not have a HR department, the interview was conducted with an employee familiar with the recruiting process. The response rate was 4 percent. The low response rate is expected for a 30-minute phone survey conducted with HR representatives.

Around 52 percent of surveyed companies are located in the Southeast region, 19 percent in the Northeast, 17 percent in the South, 9 percent in the Central West, and 3 percent in the North. About 18 percent of firms belong to manufacturing sector, 4 percent to transportation, and 16 percent to wholesale or retail. The distribution of firms in terms of industry and location is similar to the national sample (see Table A2 from Szerman (Forthcoming)).

F.2 Survey Questions

The survey is divided into five complementary parts. The first part of the survey has questions related to affirmative action support. I ask respondents to rate on a four-point scale, in which 1 is "disagree" and 4 is "agree a lot", how much they agree that: (i) "women should have preference in hiring in the labor market"; (ii) "black people should have preference in hiring in the labor market"; (iii) "people with disabilities should have preference in hiring in the labor market"; and (iv) "hiring quotas for people with disabilities should exist". I randomize the order of questions and the appearance of one of the last two questions.

The second part of the survey consists of questions adapted from Alfaro-Urena et al. (2021). I ask respondents to select up to three alternatives about: (i) "which are the most important aspects your company uses to select highly qualified workers (e.g., managers, engineers, and administrators)"; (ii) "which are the most important aspects your company uses to select less qualified workers (e.g. operators, packers, and janitorial staff)"; and (iii) "which are the most important aspects your company uses to select workers with disabilities". The alternatives are: (a) curriculum vitae; (b)

[44] The next version of the survey will be conducted with a larger sample. I exclude firms with less than 50 employees from the initial sampling process.

letters of recommendation or references from former employers or teachers; (c) immediate availability; (d) test of cognitive, psychometric, or psychological skills; (e) test of knowledge or professional skills related to the job; (f) evaluation during the probationary period; (g) interviews or tests using English or other languages; (h) criminal records; and (j) availability of infrastructure or assistive technologies. I also randomize the order of questions.

The third part includes a vignette experiment describing a big fictitious consultancy that would like to hire someone for an entry-level job to do routine clerical and organizational tasks. The vignette introduces Rafael, a 22-year-old man who finished high school, has flexibility, proactivity, and good organization skills, and interacts well with people. For some respondents, I randomize the information that this man has a bilateral hearing loss. This disability is chosen because it does not require accommodation costs or interfere in productivity for this position. I then ask respondents to rate on a four-point scale, in which 1 is "unlikely" and 4 is "very likely", how likely they think that the company would be interested in hiring him and how likely they think that he would accept the job.

In the fourth part, adapted from Domzal et al. (2008), I add questions about employer perspective on the employment of people with disabilities. I ask respondents how likely they agree on a four-point scale, in which 1 is "disagree" and 4 is "agree a lot", that the following issues represent barriers to hire workers with disabilities at the company: (i) lack of knowledge or information about people with disabilities; (ii) accommodations and barriers during the hiring process; (iii) attitudes of co-workers; (iv) attitudes of supervisors; (v) fear of absenteeism; (vi) accommodation costs; (vii) cannot find qualified people with disabilities; and (viii) nature of the work cannot be performed by people with disabilities. In option (vi), I also ask respondents to provide examples of accommodations costs that the company incurred in order to hire a worker with disabilities.

I next describe some concerns about people with disabilities often heard from employers. I ask respondents to rate on a four-point scale, in which 1 is "disagree" and 4 is "agree a lot", how much they agree that each concern is important at the company: (i) supervisors are not comfortable managing people with disabilities; (ii) supervisors are not sure how to evaluate a person with a disability; (iii) co-workers are not comfortable with colleagues with disabilities; (iv) workers with disabilities lack the skills and experience to do their jobs; (v) workers with disabilities might not be as safe and productive as other workers without disabilities; (vi) it costs more to hire a worker with disabilities due to additional management time; and (vii) negative stigma associated with hiring quota for workers with disabilities.

I further outline some strategies that companies use to hire workers with disabilities. I interrogate how much respondents agree on a four-point scale, in which 1 is "disagree" and 4 is "agree a lot", that the following strategies are useful to reduce barriers to hire workers with disabilities: (i) using recruitment agency specialized in people with disabilities; (ii) creating a diversity committee and training existing staff; (iii) increasing availability of assistive technologies; (iv) flexible working hours; (v) fiscal incentives, such as subsidies and tax deductions; and (vi) more labor inspections.

In the fifth part of the survey, I introduce open questions about performance of the last hire with disabilities relative to the peers at the company, whether accommodations were provided to this worker, and employer perceptions about what and who trigger labor inspections to better understand the mechanisms behind worker-level results.

F.3 Survey Responses

I discuss the survey results in two ways. First, I report average means of the responses across control and treatment groups, which represent firms without and under AA quota requirement (i.e., firms with less and more than 100 employees). Second, I present differential responses between these two groups after estimating the following regression:

$$R_{ij} = \alpha + \beta \times \mathbf{1}(\text{Quota}_i \geq 100) + \gamma_j + \epsilon_{ij}, \tag{14}$$

in which R_{ij} stands for employer i's answer in questionnaire type j; $\mathbf{1}(\text{Quota}_i \geq 100)$ is an indicator for firms with at least 100 employees; and γ_j is the questionnaire type fixed effects. The latter accounts for the fact that I randomize the order in which several questions are presented. The coefficient of interest, β, captures the average difference in responses between firms without and under the AA quota regulation.

Affirmative Action Support. Panel A of Table F2 displays results for affirmative action support. Compared to black people and women, respondents are, on average, more likely to support preference in hiring for people with disabilities. There is no significant differences across AA quota regulation requirement as the p-values range from 0.399 to 0.889.

Vignette Experiment. Table F1 reveals results for the vignette experiment.[45] Respondents are, on average, less likely to express interest in hiring a fictitious candidate with disabilities relative to

[45] For the vignette experiment, I consider a different specification:

$$R_{ij} = \alpha + \beta_1 \times \mathbf{1}(\text{Quota}_i \geq 100) \times \mathbf{1}(\text{Has Disability}_i = 1) + \beta_2 \times \mathbf{1}(\text{Quota}_i \geq 100) + \beta_3 \mathbf{1}(\text{Has Disability}_i = 1) + \gamma_j + \epsilon_{ij}, \tag{15}$$

in which the set of variables is the same as in Equation (14) and 1(Has Disability_i = 1) stands for employer i's question receiving randomized information on disability.

a similar counterpart without disabilities. There is no differences in the likelihood that fictitious candidate will accept the position.

Most Important Aspects to Select Workers. Table F3 presents means and point estimates for the most important aspects to select highly skilled, less skilled, and disabled workers. Curriculum Vitae (CV) is the most important factor for these three groups of workers. Some additional patterns emerge. First, the most important factors to hire workers with disabilities resemble more the ones to hire less skilled than factors to recruit highly skilled workers. Second, around 34 percent of employers report the availability of infrastructure or assistive technologies as an important factor. However, there are no significant differences across AA quota groups (p-value = 0.848). Third, firms under the AA quota are more likely to use the probationary period (p-value = 0.003) and less likely to use knowledge tests as factors to select workers with disabilities (p-value = 0.089). Fourth, although larger firms are more likely to use CV to select highly (p-value = 0.021) and less skilled workers (p-value = 0.034), such differential pattern is not evident for people with disabilities (p-value = 0.257).

Employer Perceptions. Panel B of Table F2 reveals challenges in hiring people with disabilities. On average, the most relevant challenges are the following: lack of knowledge or information about people with disabilities, inability to find qualified people with disabilities, and accommodations and barriers during the hiring process. These patterns seem consistent with employers having more challenges to interpret signals from people with disabilities. In addition, as an indirect evidence of lower hiring standards to recruit more workers with disabilities (Coate and Loury (1993)), firms under AA quota are more likely to report that they cannot find qualified workers with disabilities (p-value = 0.090). Respondents rate less attitudes of co-workers and supervisors as challenges, though firms under AA quota are more likely to report attitudes of co-workers and supervisors as challenges (p-values of 0.000 and 0.016).

In Panel C, turning to concerns about workers with disabilities at the company, supervisors who are not sure how to evaluate a person with a disability appear as the most relevant concern, followed by supervisors who are not comfortable managing workers with disabilities. Furthermore, firms under the AA quota are also more likely to report that people with disabilities might not be as safe and productive as other workers without disabilities (p-value = 0.015), workers with disabilities require additional management time (p-value = 0.080), and co-workers are not comfortable with colleagues with disabilities (p-value = 0.056). These pieces of evidence also point to a lower average skill level among workers with disabilities.

Lastly, Panel D illustrates the most relevant strategies to reduce barriers in hiring people with disabilities. Respondents tend to disagree that more frequent labor inspections and flexible working hour would represent important strategies. Interestingly, there is no evidence that firms under the AA quota are more likely to report investments in screening capital (e.g., specialized recruitment agencies) and workplace accommodations (e.g., increasing availability of assistive technologies) as relevant strategies. If anything, firms under the AA quota are *less* likely to agree that specialized recruitment agencies as relevant strategies (p-value = 0.035).

Open Questions. The survey asks how likely respondents think on a four-point scale, in which 1 is “disagree” and 4 is “agree a lot”, that inspections are triggered by employees. I find that 41.67 percent of respondents report to be likely or very likely. When asked who they think that made these complaints, incumbents with disabilities are never mentioned.

Table F1: Survey: Vignettes

	(1) Hire	(2) Accept
Above 100 emp.	-0.093	0.019
	(0.193)	(0.169)
Has Disability	-0.723**	-0.150
	(0.309)	(0.301)
Has Disability x Above 100 emp.	0.403	0.291
	(0.271)	(0.259)
Mean Dep. Var (Control)	3.26	3.19
Mean Dep. Var (Treated)	3.34	3.34

Note: Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports differences in responses in the vignette experiment after estimating Equation (15), along with mean survey answers for firms with less and more than 100 employees.

Table F2: Survey Responses: Affirmative Action Support and Employer Perceptions

	(1) Mean (Control)	(2) Mean (Treated)	(3) Pt. Est. (Std. Err.)
Panel A: Affirmative Action Support			
Women should be given preference in hiring	2.32	2.33	0.005 (0.271)
Blacks should be given preference in hiring	2.19	2.23	0.036 (0.254)
People with disabilities should be given preference in hiring	3.06	2.71	-0.327 (0.382)
Hiring quota for people with disabilities should exist	3.33	3.46	0.125 (0.229)
Panel B: Challenges in Hiring People with Disabilities			
Lack of knowledge or information about people with disabilities	2.59	2.46	-0.126 (0.236)
Accommodations or barriers during the hiring process	2.16	2.41	0.236 (0.262)
Attitudes of co-workers	1.37	2.17	0.812*** (0.202)
Attitudes of supervisors	1.40	2.00	0.580** (0.233)
Fear of absenteeism	1.45	1.76	0.327 (0.204)
Not knowing how much accommodation will cost	1.61	1.62	-0.005 (0.218)
Cannot find qualified people with disabilities	2.22	2.69	0.442* (0.257)
Nature of the work cannot be performed by people with disabilities	1.68	1.76	0.096 (0.210)
Panel C: Concerns for the Company			
Supervisors are not comfortable managing people with disabilities	1.70	2.00	0.312 (0.215)
Supervisors are not sure how to evaluate a person with a disability	2.03	2.03	-0.025 (0.258)
Co-workers are not comfortable with colleagues with disabilities	1.33	1.76	0.400* (0.205)
Workers with disabilities lack the skills and experience to do their jobs	1.35	1.55	0.192 (0.204)
People with disabilities may not be as safe and productive as other workers	1.48	2.00	0.558** (0.222)
It costs more due to additional management time	1.57	1.90	0.366* (0.205)
Negative stigma associated with hiring quota for workers with disabilities	1.74	1.76	0.038 (0.229)
Panel D: Strategies to Reduce Barriers in Hiring People with Disabilities			
Specialized recruitment agencies	3.06	2.62	-0.442** (0.205)
Diversity committee and training existing staff	2.84	2.83	0.029 (0.205)
Increasing availability of assistive technologies	2.84	2.75	-0.108 (0.195)
Flexible working hours	2.32	2.59	0.269 (0.230)
Fiscal incentives, such as subsidies and tax deductions	2.68	2.79	0.120 (0.249)
More labor inspections	2.32	2.28	-0.038 (0.266)
N	29	31	

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports mean survey answers by AA quota regulation requirement (Columns (1) and (2) for firms with less and more than 100 employees) and point estimates after estimating Equation (14), along with standard errors (in parentheses).

Table F3: Survey Responses: Most Important Factors to Hire Workers

	(1) Mean (Control)	(2) Mean (Treated)	(3) Pt. Est. (Std. Err.)
Panel A: Three Most Important Factors to Select People With Disabilities			
Curriculum Vitae	0.63	0.76	0.132 (0.115)
Letters of recommendations or references from former employers/teachers	0.33	0.21	-0.132 (0.121)
Immediate availability	0.10	0.21	0.098 (0.099)
Test of cognitive, psychometric, or psychological skills	0.17	0.10	-0.063 (0.093)
Test of knowledge or professional skills related to the job	0.40	0.21	-0.205* (0.119)
Evaluation during the probationary period	0.37	0.76	0.385*** (0.123)
Interview or test using English or other languages	0.17	0.17	0.010 (0.101)
Criminal records	0.10	0.07	-0.029 (0.077)
Availability of infrastructure or assistive technologies	0.30	0.38	0.073 (0.133)
Panel B: Three Most Important Factors to Select Less Skilled Workers			
Curriculum Vitae	0.74	0.93	0.195** (0.090)
Letters of recommendations or references from former employers/teachers	0.48	0.25	-0.244** (0.119)
Immediate availability	0.39	0.32	-0.083 (0.114)
Test of cognitive, psychometric, or psychological skills	0.16	0.14	-0.010 (0.098)
Test of knowledge or professional skills related to the job	0.23	0.21	-0.024 (0.103)
Evaluation during the probationary period	0.39	0.57	0.190 (0.133)
Interview or test using English or other languages	0.16	0.18	0.024 (0.093)
Criminal records	0.10	0.14	0.044 (0.086)
Panel C: Three Most Important Factors to Select Highly Skilled Workers			
Curriculum Vitae	0.65	0.86	0.240** (0.101)
Letters of recommendations or references from former employers/teachers	0.42	0.65	0.130 (0.117)
Immediate availability	0.13	0.17	0.019 (0.087)
Test of cognitive, psychometric, or psychological skills	0.32	0.38	0.067 (0.124)
Test of knowledge or professional skills related to the job	0.48	0.45	-0.058 (0.134)
Evaluation during the probationary period	0.48	0.28	-0.202 (0.129)
Interview or test using English or other languages	0.16	0.21	0.043 (0.102)
Criminal records	0.13	0.07	-0.058 (0.076)
N	29	31	

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports mean survey answers by AA quota regulation requirement (Columns (1) and (2) for firms with less and more than 100 employees) and point estimates after estimating Equation (14), along with standard errors (in parentheses).

G Framework: Welfare Effects of Enforcement of AA Quota with Imperfect Compliance

G.1 Model Derivations and Discussion

Decision Trees. Figures G1 and G2 illustrate firm and individual choices.

Figure G1: Decision Tree with Firm Payoffs

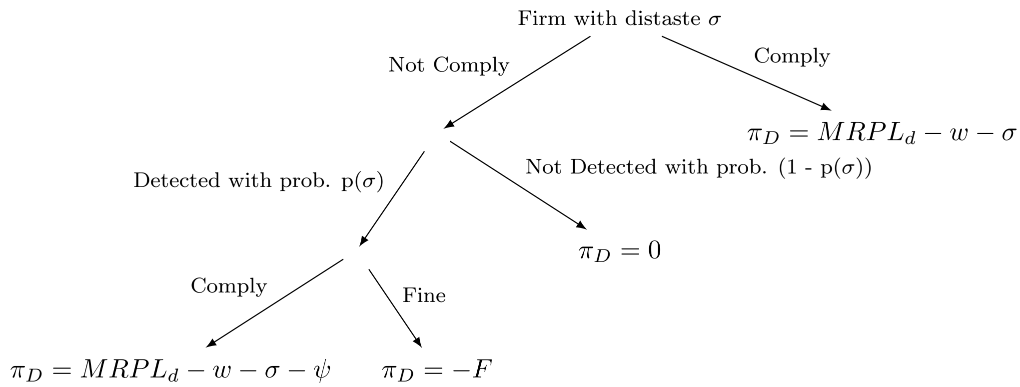
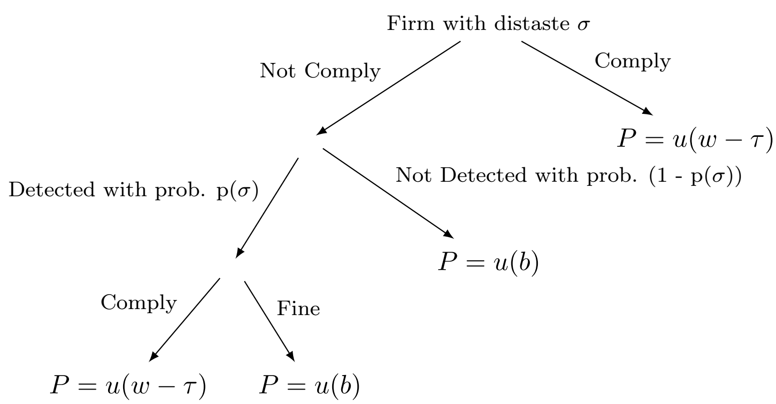


Figure G2: Decision Tree with Individual Payoffs



Enforcement and Welfare. An increase in the probability of detection $p(\sigma^*)$ impacts the expected payoff associated with non-compliance, thereby affecting the expected utility of inframarginal firms. The welfare impacts of a small change in enforcement can be expressed as:

$$\frac{\partial V}{\partial \sigma^*} = M_C[u(w - \tau) - v(b)], \tag{16}$$

in which $M_C \equiv \int_{\sigma^c}^{\sigma^F} \frac{\partial p(\sigma^*)}{\partial \sigma^*} f(\sigma)\, d(\sigma)$ represents the mass of inframarginal firms who choose compliance instead of delinquency due to a small change in enforcement.[46] We note that the welfare impacts summarize the changes in individual surplus of people with disabilities due to the increase of the number of individuals being employed in the formal sector instead of receiving welfare benefits.

Analogously, the impacts on firm profits can be written as follows:

$$\frac{\partial \Pi}{\partial \sigma^*} = (M\tilde{RP}L_d - w)M_C - M_F F, \tag{17}$$

in which $M_F \equiv \int_{\sigma^F}^{1} \frac{\partial p(\sigma^*)}{\partial \sigma^*} f(\sigma)\, d(\sigma)$ is the mass of firms that get fined. The impacts on producer surplus incorporate the changes in surplus weighted by the amount of fines paid ($M_F F$) and the difference between the marginal revenue product and wages paid to the new hires with disabilities $(M\tilde{RP}L_d - w)M_C$.

Finally, the effects on revenues can be expressed in the following way:

$$\frac{\partial R}{\partial \sigma^*} = M_C[\tau + b] + M_F F, \tag{18}$$

in which the marginal revenue benefit is the revenue raised from higher employment ($M_C[\tau - b]$) and fines ($M_F F$).

Optimal Enforcement Policy. The government sets enforcement level σ^* that maximizes the following social welfare function:

$$W(\sigma^*) = V(\sigma^*) + \Pi(\sigma^*) - C(\sigma^*). \tag{19}$$

Under standard regularity conditions, the first-order condition can be written as:

$$\underbrace{V'(\sigma^*)}_{\text{marginal welfare benefit}} = \underbrace{C'(\sigma^*)}_{\text{marginal cost of enforcement}} - \underbrace{\Pi(\sigma^*),}_{\text{marginal producer loss}} \tag{20}$$

in which the government chooses enforcement level to set its marginal benefit equal to marginal cost. Put differently, the government trades off the overall marginal private benefits of higher

[46] The policy has no welfare change from firms that always abstain from compliance regardless of enforcement level. In addition, due to the envelope theorem, the policy also has no welfare change from firms that always comply with the regulation regardless of enforcement level.

employment of people with disabilities against the marginal cost of conducting inspections and the marginal lost surplus to firms. Because the empirical results indicate that people without disabilities are unaffected, there is no welfare change for them.

If the government also uses higher enforcement level to raise additional fiscal revenues $R(\sigma^*)$ (e.g., to increase the provision of public goods), the first-order condition can be alternatively be written as:

$$\underbrace{V'(\sigma^*)}_{\text{marginal welfare benefit}} + \underbrace{R'(\sigma^*)}_{\text{marginal revenue benefit}} = \underbrace{C'(\sigma^*)}_{\text{marginal cost of enforcement}} - \underbrace{\Pi'(\sigma^*),}_{\text{marginal producer cost}} \tag{21}$$

in which the marginal revenue benefit enters in the left-hand side and indicates that the government is willing to tolerate larger welfare loss to firms when setting the optimal enforcement. If the marginal costs exceed the extra revenues raised, the government must weigh the deadweight loss against the marginal benefits of increasing enforcement level.

Plugging Equations (16), (17), and (18) into Equation (21), we have that:

$$\underbrace{M_C[u(w-\tau) - v(b)]}_{\text{marginal welfare benefit}} + \underbrace{M_C[\tau + b]}_{\text{marginal revenue benefit}} = \underbrace{C'(\sigma^*)}_{\text{marginal cost of enforcement}} + \underbrace{(w - M\tilde{RPL_d})M_C}_{\text{marginal producer cost}}. \tag{22}$$

All objects can be obtained from the data and the reduced-form estimates. The first term — the marginal welfare benefit — depends on the utility cost of employment. The marginal revenue benefit can be directly obtained from the Census data. The marginal cost of enforcement can be bounded by the average cost of inspections. The marginal producer loss can be computed even without data on firm outcomes through a simple discrete choice framework, which I discuss in detail in Section 6.2. I also propose an alternative approach to back out a "break even" producer loss.

Incumbents with Disabilities. Thus far, the model does not distinguish between new hires and incumbents with disabilities and assumes fixed wages. However, the empirical analysis indicates that firms adjust through lower wage growth for incumbent workers. In this setting, with linear utility functions, it represents a simple lump-sum transfer from people with disabilities and government to firms. This implies that the government only needs to trade off marginal benefits and marginal producer loss from new disabled hires when evaluating total welfare. Likewise, revenue from fines represents a lump-sum transfer from firms to the government in linear functional forms.

Marginal Welfare Benefit. To overcome the lack of data on consumption and assets and get a tractable expression, I assume hand-to-mouth agents so that consumption tracks net income. This assumption is reasonable in this context. I also consider the flow of income, implying that my estimates are very conservative and reflect the lower bound of the benefit side. I take two approaches to derive bounds on the marginal welfare benefit. First, to get an upper bound to the cost of employment, I assume that unemployed individuals do not have marginal disutility from working. In this case, I can approximate the marginal benefit as an extensive margin choice of employment and, therefore, an income flow of a switch from welfare benefits to employment. From the 2010 Census, I calculate that, on average, a worker with disabilities in the formal sector makes 22,660 *reais* every year and, as a result, is subject to an income tax rate of 7.5 percent. Each person with disabilities not employed in the formal sector receives 3,827.16 *reais* in welfare benefits. Given the 41.7 percent increase in the number of employees, together with the baseline average of 0.29, the marginal welfare benefit associated with additional hires is 870.21 *reais*.

Second, to get a lower bound to the cost of employment, I need a parameter representing the utility cost of switching from employment to welfare benefits, which directly depends on the opportunity cost of a full-time job due to lost leisure. In this case, I follow Mas and Pallais (2019) and assume that the value of non-work time relative to labor earnings is 0.58. The estimated marginal welfare benefit is 372.65 *reais*.

Marginal Cost of Enforcement. Because there are no data available on inspection-specific spending, I consider the average cost of inspections as an upper bound for the marginal cost of inspections. According to the Federal Budget Panel (*Painel do Orçamento Federal*), the average annual budget of labor inspected (deflated to 2018 prices) is 27,787,724 Brazilian *reais*. Considering that the total number of inspections per year is about 279,857, each inspection costs around 99.29 *reais*. It is possible to consider alternative enforcement policies to boost compliance with regulation, such as data-driven inspections and threat-of-audit letters, that would target non-compliant firms more directly. While these targeted policies are likely to reduce the costs of inspections in the long term, implementing them would also impose its own costs.

Marginal Revenue Benefit. The marginal fiscal gain is the sum of revenues raised with income tax and saved with welfare benefits from new hires. The marginal revenue benefit is 668.34 *reais*.

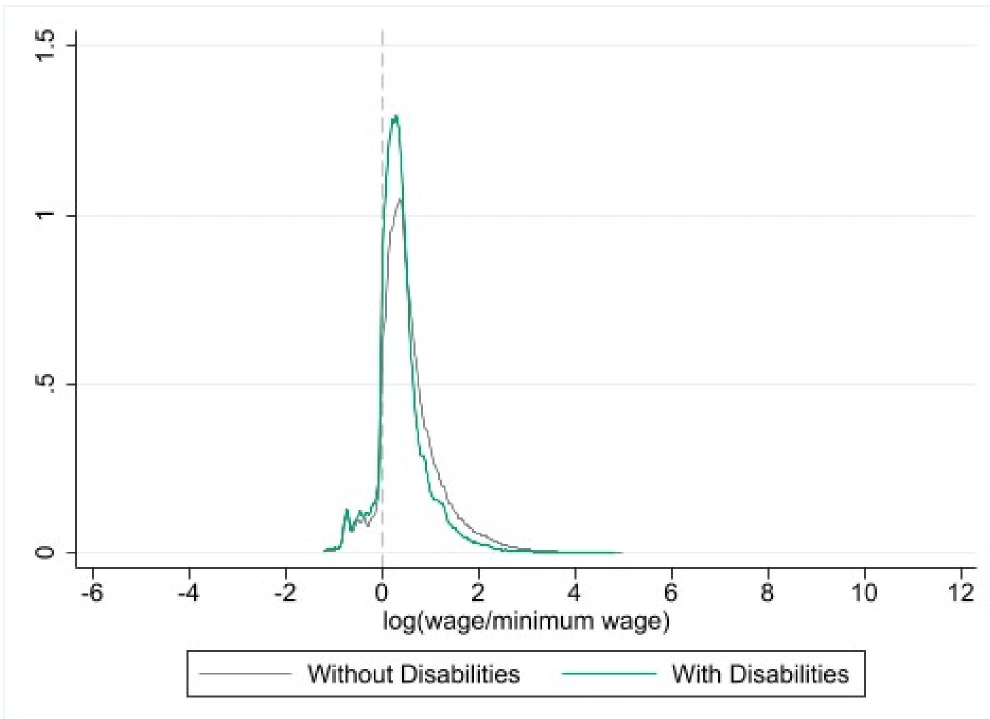
Marginal Producer Cost. Due to lack of data on profits, changes in producer surplus cannot be directly inferred. Instead, I rely on two indirect approaches to construct bounds for the marginal producer loss. First, I use reduced-form estimates to back out a "break even" producer cost that sets marginal welfare benefits equal to marginal costs from Equations (20) and (22). Table G1 reports the "break even" values of average ratio between marginal revenue product of labor and average wages considering different scenarios. Each row indicates whether opportunity cost of work and fiscal revenue benefit are accounted for in the calculation. Even in the most conservative scenario, the ratio is below one, pointing to social benefits exceeding social costs. The second approach involves using the discrete choice framework, which is discussed in detail in Section 6.2.

Table G1: Cost-Benefit Analysis

(1) Opport. Cost of Work	(2) Revenue Benefit	(3) Break-Even MRPL/w
No	Yes	0.6563
Yes	Yes	0.4748
No	No	0.7187
Yes	No	0.9002

Note: This table reports a range for "break-even" values of $M\tilde{R}PL$, normalized by average wages, that set marginal welfare benefits equal to marginal costs of increasing enforcement of AA quota from Equation (12).

Figure G3: Monthly Wage Distribution among Workers in the Private Sector



Note: Graph illustrates kernel densities (Epanechnikov kernel with a bandwidth of 0.025) of the log wage-to-minimum wage ratio for people without and with disabilities separately. The sample is restricted to workers in firms with at least 100 employees. Source: RAIS data.