Internal Migration and Labor Market Adjustments in the Presence of Nonwage Compensation

Raphael Corbi* Tiago Ferraz† Renata Narita‡

May 17, 2021

Abstract

We investigate the labor market impacts of internal migration in Brazil between 1996 and 2010 using a shift-share approach which combines weather-induced migrant flows from the Semiarid region with the past settlement patterns in each destination based on the migrant's region of origin. Our results indicate that increasing yearly internal migration rate by $1p.p.$ reduces formal employment of natives by $0.30p.p.$, while increases the number of informal jobs by $0.15p.p.$ and self-employment by $0.10p.p.$ The lack of effect on overall employment can be explained by workers reallocating to informality, as well as compensation adjustments through wages and benefits. Consistent with downward wage rigidity in the formal sector, we find no effect on earnings but a negative impact on the share of workers receiving nonwage benefits. Earnings decrease in the informal sector by 1.5% and in self-employment by 1.4%, consistent with classic predictions from perfect competition and the fact that migrants and low skilled natives are close substitutes. In particular, less educated individuals appear to bear most of the welfare losses, both in terms of overall earnings and in offered nonwage benefits.

Keywords: Internal migration, wages, employment, nonwage benefits.
JEL Codes: J2, J3, J61, O15.

*University of São Paulo, Department of Economics, Email: rcorbi@usp.br
†University of São Paulo, Department of Economics, Email: tiago.ferraz@usp.br
‡University of São Paulo, Department of Economics, Email: rnarita@usp.br
We are grateful to Rodrigo Adão, Bruno Barsanetti, Christian Dustmann, Richard Hornbeck, Peter Hull, Rudi Rocha, and conferences and seminars participants for helpful comments. The authors acknowledge financial support from FAPESP and CAPES. Raphael Corbi thanks the University of Chicago and Renata Narita thanks the Federal Reserve Bank of Chicago for their hospitality where parts of this work were completed.

1 Introduction

Migration, both within and beyond borders, has become an increasingly prominent topic in the international debate. There is now a large literature on the impacts of migration on the native population in terms of employment and wage levels. In a recent book, Borjas (2014) summarizes his vast contribution to the field and underscores the costs of immigration for competing native workers. On the other hand, a raising fraction of scholars have concluded that migration has more nuanced effetcs (Card and Peri, 2016). Card (2009) finds that immigration to the United States has only a minor effect on native wages, and Ottaviano and Peri (2012) report small positive wage effects.

Canonical partial equilibrium models with perfect competition and substitution between natives and migrants predict full adjustment through wages when natives are immobile, or lower native employment when wages are rigid (for an early example, see Altonji and Card, 1991). Attempts to reconcile the apparently contradicting empirical evidence include expanding models to accommodate multiple outputs and technology margins (Lewis, 2011; Dustmann and Glitz, 2015), as well as recognizing that different empirical specifications measure different parameters (Dustmann et al., 2016).

While the debate remains contentious, implicit in this discussion is a common but under-considered assumption that nonwage aspects of jobs are taken as fixed. Indeed, Clemens (2021) argues that allowing for adjustment on working conditions (e.g. safety measures and flexible schedules), output prices and benefits may explain existing controversies over the economics of minimum wages. Here we argue that adjustments in margins including nonwage compensation are empirically relevant and thus can have important implications for studying the effects of labor supply shocks due to migration.

In this paper we investigate the impacts of internal migration in Brazil on the labor market outcomes of natives in a setting where downward wage rigidity is present, nonwage benefits are a relevant margin of compensation and labor informality is pervasive. This setup allows us to study how firms and workers, when adjusting to a labor supply shock due to increased migration inflows, may circumvent the binding minimum wages by reducing nonwage benefits of formal jobs, or may simply lower salaries in unregulated informal markets.

Brazil provides a good environment for our investigation for three reasons. First, over 3 million people in the Brazilian Semiarid, a historical source of climate migrants, left their hometowns during our sample period of 1996-2010. Second, a within-country analysis minimizes econometric concerns about allocating migrants to particular skill groups (Dustmann et al., 2012). Third, over 40 percent of workers are employed in the less frictional informal labor sector, where firms do not comply with labor market statutes, such as minimum wage laws and firing regulations. The rest of the workforce participates in the formal sector where minimum wage is binding (above 70% of the median wage) and nonwage compensation is frequently offered. Indeed, over 31 million people or 20% of registered workers are covered through employer-provided health insurance. After payroll expenses, this is the second highest component of total labor costs (ANS, 2019). Also, 40% of these workers receive food subsidy, costing firms about 57% of the minimum wage per worker.[1] To the extent that workers value nonwage benefits, changes in this important margin of adjustment can have important welfare implications.

In order to address the econometric concerns associated with the fact that migrants tend to move to areas with better labor market opportunities, we combine two extensively used identification strategies into a shift-share instrument approach. First, we exploit exogenous rainfall and temperature shocks (or "shift") at the origin to predict the number of individuals leaving each Semiarid's municipality. Then we leverage the history of the Semiarid as a large source of climate migrants and use the past settlement patterns (or "share") to allocate migration outflows to destination areas (Munshi, 2003; Boustan et al., 2010). The resulting predicted inflow of migrants is an instrument for observed migration.

Our results show that increasing the rate of migration inflows by one percentage point reduces the share of formal employment among native workers by $0.30 p.p.$, while increases the number of informal jobs by $0.15 p.p.$ and self-employment by $0.10 p.p.$ These results are consistent with a binding minimum wage such that migration shocks lead to lower formal employment as formal sector employers cannot adjust wages down, and individuals who lost their formal jobs being absorbed by informal firms or self-employment, which are more competitive labor sectors. Thus the overall effect on total employment across sectors is small.

Regarding compensation in the formal sector, we do not find an effect on earnings but do find a negative impact on the share of formal workers receiving employer-provided health insurance in the range of $0.2 p.p.$ to $0.6 p.p.$, food vouchers from $0.3 p.p.$ to $0.7 p.p.$ and transportation voucher from $0.5 p.p.$ to $0.7 p.p.$. Despite declines in the provision of non-monetary benefits, which increases labor demand, employment in the formal sector still reduces as mentioned.[2] This additional adjustment margin of firms may also explain why we find null effects on formal sector wages across the entire wage distribution and not only on bottom wages which likely explained by the minimum wage. For individuals employed in the informal sector or self-employed we show a 1.4% decrease on earnings mostly concentrated on the bottom third of the wage distribution, consistent with classic predictions from perfect competition and less skilled migration.

Heterogeneity analysis shows that all effects are stronger for less educated native workers, which is consistent with the fact that they directly compete with Semiarid's migrants. When compared to those with high education, less educated natives are

[1] Arbache and Ferreira (2001) based on various sources estimate the average cost of providing some job benefits in Brazil.

[2] Recent literature, as discussed in Clemens (2021), reports a negative correlation between minimum wage increases and health insurance provision, with the variation of this benefit offsetting about 15% of the cost with minimum wage increases.

30% more likely to exit the formal sector and experience a 40% greater wage reduction. Moreover, as more low education workers earn close or equal to the minimum wage, the negative impact on the most frequently nonwage benefits provided by firms is greater for them. This suggests that welfare declines more for low income workers therefore rising welfare inequality among natives.

Finally, we find that labor force participation increases by $0.14 p.p.$ which may seem at odds with previous results since earnings fall in the informal sector and self-employment, and lower benefits are paid in the formal sector. By running separate regressions for head and non-head of the household, we find that almost all the impact on the employment margins comes from head of household workers, while the change in unemployment and inactivity rates are led by the non-head member, consistent with the added worker effect (Lundberg, 1985).[3]

Our work is related to the wide literature that examines the impact of migration flows on labor market outcomes of natives (see Borjas, 2014 and Dustmann et al., 2016 for a review). Despite the fact that migration within countries is a larger phenomenon according to some estimates, most studies are concerned with international immigration to high-income countries, with particular attention given to Mexican immigration to the United States (Borjas, 2003) and, more recently, to immigration to Western Europe (Dustmann et al., 2012).[4] Some of these studies find that the wages of natives are harmed by immigration (Borjas and Monras, 2017), while others find only a minor negative effect on native wages (Card, 2001), or even positive (Ottaviano et al., 2013; Foged and Peri, 2016).[5] A smaller set of studies explore environmental shocks to study the causal impact of internal migration on local labor markets in the US (Boustan et al., 2010; Hornbeck, 2012).[6] More closely related to our work is Kleemans and Magruder (2018) who study the impacts of internal migration in a developing country, Indonesia, from a two-sector labor market perspective. They show that internal migration reduces employment in the formal sector and earnings in the informal sector.[7]

Our contribution to the economics of migration literature is threefold. First, we show that accounting for adjustments in nonwage compensation in response to labor supply shocks are key to understanding the effects of migration on natives. Second, we provide evidence on the effects of internal migration on local labor markets in a large developing

[3]The "added worker effect" in a broader sense here refers to an increase in the labor supply of secondary earners (typically wives and children) when the primary earner (husbands) becomes unemployed or lose a formal sector job where benefits, sometimes extended to the family, are provided.

[4]Rough estimates indicate that global internal migration sits around 740 million (UNDP, 2009), approximately three times the estimated number of international migrants (UN DESA, 2017).

[5]Dustmann et al. (2016) argue that such often contradictory estimates are a result of (i) different empirical specifications (sources of variation), as well as the fact that labor supply elasticity differ across different groups of natives, and immigrants and native do not compete in the labor market within the same education-experience cells.

[6]See also Molloy et al. (2011) for a comprehensive literature review on the determinants of internal migration in the U.S. and Lagakos (2020) on urban-rural internal movements.

[7]This approach relates to the seminal work of Harris and Todaro (1970). A similar extension and test of this model is provided in Busso et al. (2021) using census data from Brazil.

country, and show that these different adjustment patterns are relevant even in the presence of informality. Last, we add to a growing body of evidence that migration is an important coping mechanism against climate change, especially for vulnerable populations in rural areas of developing countries (Skoufias et al., 2013; Assunção and Chein, 2016).

Nonwage benefits are also an important part of compensation in developed countries. In the US, employer-provided health insurance and other benefits account for around one-third of compensation costs (Clemens et al., 2018). 74% of firms in Europe paid non-base wage components such as benefits and bonuses in 2013 (Babecký et al., 2019). Evidence shows that firms adjust nonwage components when facing adverse economic shocks (Babecký et al., 2019) or as an strategy to offset collective bargaining (Cardoso and Portugal, 2005), particularly when base wages are rigid (Babecký et al., 2012). We add to this literature by showing that nonwage benefits are an important margin of adjustment in the case of labor supply shocks due to internal migration.

In terms of empirical strategy our paper relates to many works that uses a shift-share IV approach to identify the effects of migration on a range of outcomes (e.g. Card, 2001, 2009; Ottaviano and Peri, 2012; Ottaviano et al., 2013; Cattaneo et al., 2015; Foged and Peri, 2016). In particular, we take advantage of a recent body of work that provide a clear framework for distinguishing sufficient conditions for identification according to each source of variation, and how to properly compute standard errors (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2021; Jaeger et al., 2018; Adao et al., 2019).

This paper is organized as follows. In the next section, we first present background information on the Brazilian Semiarid region and labor markets, outline a simple framework for interpreting our findings, and describe the data used in our empirical analysis. In section 3, we explain the empirical strategy and the identifying assumptions we make. In section 4, we present and analyze the main results on employment, wages and nonwage wage benefits. Section 5 considers the case in which individuals with lower levels of education may bear most of the welfare losses due to migration. Then we conclude.

2 Background

In this section, we first describe the economic background and weather conditions at the Semiarid region, the functioning of local labor markets in Brazil, and a simple framework in an effort to contextualize our analysis. We then discuss the main sources of data regarding labor market outcomes, migration flows and weather, and present some descriptive statistics.

2.1 Brazilian Semiarid

The Brazilian Semiarid encompasses 960 municipalities spread over 9 states, covering an area of around 976,000km^2.[8] According to the official definition by the Ministry of National Integration, a municipality qualifies as Semiarid if at least one of these three criteria holds: (i) annual average precipitation below 800 mm between 1961 and 1990; (ii) aridity index up to 0.5[9]; (iii) risk of drought above 60%[10]. The average historical precipitation in the Semiarid is about 780mm, as opposed to around 1,500 mm for the rest of the country[11], while average temperature is around 25°C. The rainy season occurs between November and April, with the highest levels of precipitation after February, when the sowing seasons typically starts.

Municipalities are relatively small with median population around 20,000 and have economies mainly based on agriculture and cattle ranching in small subsistence properties. Local economic activity is particularly susceptible to weather shocks (Wang et al., 2004), with some studies showing a loss of up to 80% of agricultural production in periods of long drought (Kahn and Campus, 1992). About 80% of the children lived below the poverty line and infant mortality reached 31 per 1000 births in 1996, compared to a national average of 25% and 15 per 1000 births, respectively (Rocha and Soares, 2015). More than 80% of the adult population had less than 8 years of schooling in 1991.

Such poor socioeconomic indicators associated with periods of extreme drought have historically driven large outflows of migrants - or so-called *retirantes* - from the Semiarid to other areas of the country (Barbieri et al., 2010). During the 1960s and 1970s, net migration out of Northeastern states (where most of the Semiarid is located) was 2,166,258 and 3,049,459 individuals (Carvalho and Garcia, 2002), which correspond to net migration rates of 7.6 and 8.7%, respectively. Between 1980 and 2010, around 1.9 million people left the Semiarid alone searching for better conditions elsewhere in the country. Figure A1 shows that these migrants tend to be historically concentrated in some states. São Paulo alone harbored over 30 percent of the people arriving from the Semiarid in the last four decades. However, in relative terms incoming migrants represented a population increase of above 2% for the top 10 receiving states.

2.2 Labor markets in Brazil

A common feature of labor markets in developing countries is the existence of a two-sector economy where the informal sector accounts for one to two-thirds of the GDP (see Perry et al. (2007) and Ulyssea (2020) for a review). In Brazil, over 40% of individuals work in the informal sector (those without registration or who do not contribute to social security) including the majority of the self-employed who are not

[8] That is roughly the same as the territory of Germany and France combined. The semiarid comprises 11 percent of the Brazilian territory and includes parts of almost all Northeastern states, except for *Maranhão*, plus the northern area of *Minas Gerais*, but it does not cover any state capital.

[9] Thornthwaite Index, which combines humidity and aridity for a given area, in the same period.

[10] Defined as the share of days under hydric deficit, using the period 1970-1990.

[11] See Figure 10.

protected through social security. When firms hire workers under a formal contract they are subject to several legal obligations, such as paying minimum wages and complying with safety regulations. Registration also entitles workers to other benefits such as a wage contract, which in Brazil prevents downward adjustment, working up to 44 hours weekly, paid annual leave, paternity or maternity leave, retirement pension, unemployment insurance, and severance payments (e.g. Gonzaga, 2003; Almeida and Carneiro, 2012; Meghir et al., 2015; Narita, 2020).

If firms do not comply with working regulations they may be caught by the labor authorities and have to pay a fine. For example, a firm is fined about one minimum wage for each worker that is found unregistered, or the firm can be fined up to a third of a minimum wage per employee if it does not comply with mandatory contributions to the severance fund (Almeida and Carneiro, 2012).[12] On the other hand, it is a well-known fact that compliant (formal) firms are those more visible to labor inspectors and thus subject to more inspections whereas informal firms are smaller and thus difficult to get caught (Cardoso and Lage, 2006). There are also other expected costs for formal firms associated with labor courts in case the worker is fired and decides to file a lawsuit against the firm. Judges decide in favor of workers in nearly 80% of cases (Corbi et al., 2021). All this points to a significant cost of operating in the formal sector, particularly for smaller firms. Imperfect enforcement and costly regulation are associated with high labor informality in the country.

Finally, as there is a strong overlap between the productivity distributions of formal and informal sectors (Meghir et al., 2015), even for lower percentiles of the overall distribution, both sectors should be affected by the influx of migrants. In other words, both sectors have workers who are close substitutes to the migrant workforce and thus will experience competition.

Nonwage benefits In our empirical analysis we focus on three main fringe benefits we observe in the data: private health insurance, food and transport subsidy. In Brazil, benefits became popular in the 1980s, as the provision of food subsidy and employer-provided health insurance became more frequent among private sector firms (Arbache, 1995). Data from PNAD surveys for 1996-2009 indicate that 39% of workers in the formal sector receive food subsidy, 36% receive transport subsidy and 20% get private health insurance through their employers. Arbache and Ferreira (2001) estimate that benefits like food subsidy for instance cost around 57% of one minimum wage (around 16% of average total compensation). Similarly, Brazilian Federal Health Agency data (ANS, 2018) show that employer-provided health insurance cost on average R$582 in 2018, which is 17% of total compensation in that same year. These numbers imply that depending on how firms opt to mix benefits in the workers' package, these expenses may add up above 30% of the total payroll cost. In the US, benefits including employer-provided health insurance account for around one-third of compensation costs (Clemens, 2021)

[12] The minimum wage is above 70% of the median wage in Brazil.

There are at least two reasons that can explain the use of fringe benefits in the workers' compensation. First, these benefits in Brazil are not subject to payroll taxation and therefore reduce total labor costs. Second, labor legislation is generally more flexible regarding the provision of benefits such that it is easier to adjust benefits than wages (Arbache, 1995) Even though regulations for fringe benefit provision are considered less rigid than for wages, collective bargaining agreements (CBA) sometimes include clauses pertaining fringe benefits. In particular, the third most common clause type among extended firm-level CBA includes wage supplements such as food subsidy (Lagos, 2020) Also, around 10% of all formal sector firms are under CBA with a clause on health plan/insurance (Marinho, 2020)

Although transport subsidy is a mandated benefit in Brazil since 1985, we treat this as a benefit that firms can adjust. This is likely the case since we observe that only 36% of formal sector workers report they receive this benefit. That is, firms may not fully comply with all aspects of labor regulations. Also, as transport benefit is nonwage compensation, firms do not incur in payroll taxes. In addition, firms may deduct the cost with the offered subsidy from the base for income taxation as well as from their operational cost lowering net revenue which is the base for other corporate and payroll taxation.[13] This implies that firms have incentives to offering transport benefit and a further incentive to adjust it at the intensive margin by providing better means of transportation or increasing the benefit in cash.

2.3 A simple theory

To interpret our findings, in this section we describe a simple model assuming perfectly competitive labor markets. Migration shifts the aggregate labor supply to the right in the destination region, and both migrants and natives are assumed to be perfect substitutes.

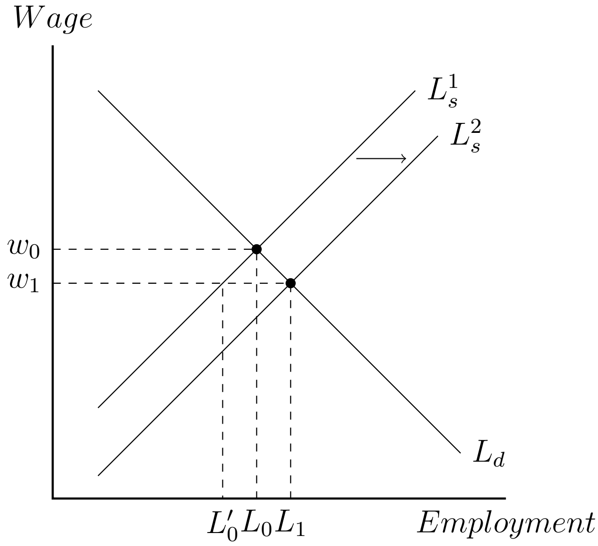
We begin by illustrating a case without institutions (e.g. minimum wages) that affect any labor market adjustment in the regulated sector and holding constant nonwage job attributes that are paid by firms. As Figure 1 shows, labor supply elasticity determines the extent to which migration affects employment vis-à-vis wages. In the extreme case in which supply is inelastic, migration negatively affects wages with no effect on employment of natives and absorbing all migrant workforce. On the other hand, with elastic labor supply, the reduction in wages make jobs less attractive for some native workers such that, at w_1, native employment reduces from L_0 to L_0'. The new equilibrium then determines the employment of migrants, L_1-L_0'.

However, in a real-world scenario, there are downward wage rigidities often imposed by minimum wage laws and collective bargaining agreements. There are also other components of labor costs that firms may adjust given wage constraints (McKenzie, 1980; Clemens, 2021).

As we introduce wage rigidities, a supply shock due to migration needs to be

[13] The income tax due cannot be reduced by more than 10%.

Figure 1: The Effects of Migration in a Perfectly Competitive Labor Market

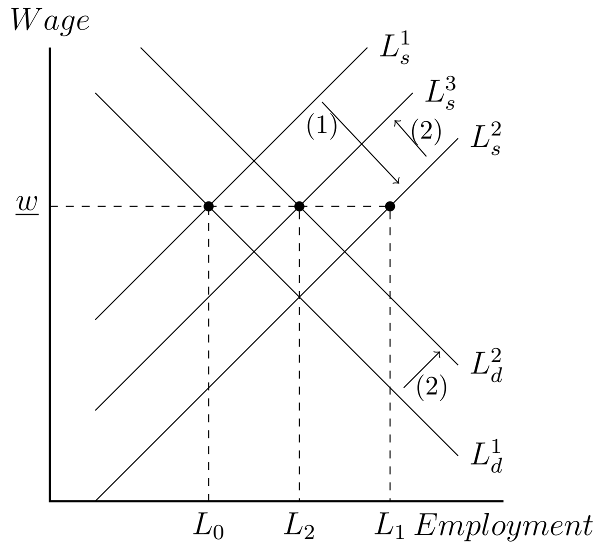


accommodated by job losses or through cutting labor costs, for example, reducing nonwage benefits, e.g. health insurance. This situation is depicted in Figure 2 starting with an economy where the minimum wage is set at the market-clearing level and a migration shock that causes unemployment of L_1-L_0. Then, as it shows, reductions in nonwage compensation can shift both the supply curve and the demand curve. For firms, lowering nonwage benefits imply a higher labor demand curve because it increases its revenue net of costs. With wages fixed at $\underline{w}$, the new level of employment is L_2. For workers, under the assumption that they value such benefits, labor supply shifts upwards which is consistent with jobs becoming less attractive to workers and with a higher wage to compensate for the loss in benefits. In this case the shift of the supply curve due to adjustments in nonwage benefits may undo the migration supply shock and may even nullify its negative effect on employment. In this special case, demand and supply shifts due to a reduction in amenities bringing the economy to a new equilibrium which pays exactly the minimum wage and employment is at L_2, where there is no unemployment. Migration in this case increases total employment in the receiving region from L_0 to L_2 however some reduction of employment among natives may occur. Importantly, this reduction comes from some workers withdrawing the labor market since they are not willing to work at the lower benefit level.

In sum, in a simple competitive model with no rigidities, which is likely closer to the informal (unregulated) sector case, we expect some negative effects on wages and an increase in total employment. The effects on employment of natives depend on the labor supply elasticity. As we expand this simple model to consider both minimum wage regulations and the possibility of adjustment in nonwage benefits by firms, we find that the model yields ambiguous predictions regarding unemployment. The key aspect that determines this result is the valuation of benefits by workers compared to the cost of providing such benefits by firms.

Empirically, we expect these forces to be true mostly for low-skill workers or those

Figure 2: The Effects of Migration with Binding Minimum Wages and Perfect Adjustment of Nonwage Benefits



NOTE: This figure extends the standard competitive labor market case presented in figure 1 to allow for downward wage constraints e.g. minimum wages ($\underline{w}$) and adjustments in nonwage benefits in response to the labor supply shock due to migration.

at the bottom-medium but not at the top of the formal wage distribution. Low-skilled workers are the most affected by the migration shock since migrants are generally low-skilled.[14] Their wages are more affected by minimum wage policies and collective bargaining agreements but also benefits such as health insurance and food are disproportionately more generous for low than for high skill workers. Of course, since many firms or many industries combine both high and low skilled workforce there might be spillover effects to the former group due for example to complementarities, but empirically we expect the effects on high skilled workers to be of second order.

Finally, particularly in labor markets in developing countries, if jobs become rationed in the formal sector due to e.g. binding minimum wages, then workers may find an opportunity and choose to work in the informal sector in which case unemployment may not increase and informal sector wages are expected to go down, consistent with predictions from perfect competition.

3 Data and Identification

In this section, we first describe the empirical framework that allows us to (i) isolate the observed variation in migration induced by exogenous weather shocks, and (ii) the migration flows into destination municipalities determined by past settlements. We then discuss and present supportive evidence on the validity of this shift-share instrument

[14] This follows the arguments developed by the labor market model in Card and Lemieux (2001) and Borjas (2003).

approach based on insights of the recent econometric literature that analyzes its formal structure.

3.1 Migration, labor market and weather data

We draw data from three waves of the Brazilian Census (1991, 2000 and 2010), provided by the *Instituto Brasileiro de Geografia e Estatística (IBGE)*, to construct two of the main variables used in out study.[15] First, we leverage Census answers about municipality of origin and year of migration, we construct a measure of yearly migration outflow from each municipality in the Semiarid and a measure of inflow to each destination (all but Semiarid) during the 1996-2010 period. Second, we use the 1991 Census to build a "past settlement" measure by associating the share of migrants from each Semiarid municipality who resides in each destination.[16]

Weather data were retrieved from the Climatic Research Unit at University of East Anglia (Harris et al., 2020). The CRU Time Series provides worldwide monthly gridded data of precipitation and temperature, at the $0.5^\circ \times 0.5^\circ$ level (0.5° is around 56km on the equator). We construct municipality-level monthly precipitation and temperature measures based on grid-level raw data as the weighted average of the municipality grid's four nodes using the inverse of the distance to the centroid as weights.[17] We define the rainfall shocks as deviations from the historical average. More specifically

$$Rainfall_{ot} = \ln\left(\sum_{\tau \in \{GS\}} r_{o\tau t}\right) - \ln(\bar{r}_o) \tag{1}$$

where $r_{o\tau t}$ is the rainfall in municipality of origin o in month τ of year t, and $\bar{r}_o$ is the municipality's historical average precipitation for the same months. The index τ covers the Semiarid's 6-month growing season (GS) period.[18] Historical averages are calculated over the period from 1901 to 2010. Temperature shocks are computed in a similar way, using average temperatures instead of the summation.

We use labor market outcomes data from *Pesquisa Nacional por Amostra de Domicílios* (PNAD) - a major household survey also conducted by the *IBGE* - which covers 808 municipalities in all 27 states. Even though PNAD municipalities do not cover the whole country, they are the destination choice of about 80% of the migrants who leave the Semiarid and are home to more than 65% of the employed population in Brazil. The survey is conducted every year, except in Census years. Thus we have data from 1996 to 1999 and from 2001 until 2009. We restricted our attention to individuals between 18

[15] As several municipalities were split into new ones during the 1990s, we aggregate our data using the original municipal boundaries as they were in 1991 (so-called "minimum comparable areas" or AMC) in order to avoid potential miscoding regarding migration status or municipality of origin. We use terms municipality and AMC as synonyms throughout the paper.

[16] See Appendix A for a detailed explanation of how we build these variables.

[17] This approach is similar to the one used by Rocha and Soares (2015).

[18] We also calculated this measure using the 12 months of the year (see discussion in Apendix B). Results are virtually the same.

and 65 years old, living in the municipality for 10 years or more and we refer to them as *natives*. We consider destination all PNAD municipalities that are not in the Semiarid in order to minimize concerns about spatial correlation in weather shocks.

Our main outcomes come from data on earnings and indicators for employment; whether the worker is an employee in the formal sector (registered with the Ministry of Labor), informal sector or self-employed; whether she is unemployed or out of the labor force. We also create indicator variables for some forms of nonwage compensation. The survey asks specifically whether the individual received any kind of payment or help to cover expenses with food, transport and if the job provides health insurance. Finally, we pool the 13 years of individual survey data the survey and take averages at the municipality-year level. The final destination sample has 2,153,328 individuals at 684 unique municipalities and 8,190 municipality-year observations.

Table 1 describes municipality-level data for origin (Panel A) and destination (Panel B) municipalities. Semiarid's areas show lower levels of rainfall, slightly higher temperatures and are less populated than destination municipalities. On average, 1.0 p.p. of Semiarid's population leave every year, resulting on average increase of 0.27 p.p. of the labor force in the destination.

Table 2 provides descriptive statistics for destination municipalities. In our sample, 63% of individuals are employed - with 32% having a formal job, 16% having an informal job and 16% being self-employed. Unemployment rate is 13% and 24% of individuals are not in the labor force. The average monthly earning is R$ 637.87, with the formal sector having a substantially higher avrage (R$ 788.18) than the informal sector (R$ 382.31) and a little higher than for the self-employed (R$ 600.83).[19] Among workers employed in the formal sector, 39% receive financial help to cover expenses with food, 36% for transport and 20% for health expenditures.[20]

Finally, Table 3 compares migrants to low and high education natives. Migrants are slightly more educated and earn slightly less than low educated natives. They also have similar likelihood of working part time and being in the formal sector when compared to low education natives. On the other hand, high education natives are more likely to work in the formal sector, and have considerably higher pay. Table A1 shows that top occupations for migrants (e.g. typically bricklayer for men, domestic worker for women) are also top occupations for low education natives, but not for the skilled. Also, the same five industries that concentrate over 80% of working migrants also employ a similar share of low education workers (see Table A2). Overall, this characterization is consistent with greater substitutability between migrants and less skilled natives in the labor market.

[19] Earnings are measured in R$ (2012).

[20] Less than 1% of informal and self-employed workers receive any kind of nonwage compensation.

3.2 Main specification and identifying assumptions

We specify a model for the changes in labor market outcomes of native individuals as a function of internal migration flows. Specifically we assume that

$$\Delta y_{dt} = \alpha + \beta m_{dt} + \gamma \Delta X_{dt} + \psi_t + \epsilon_{dt} \tag{2}$$

where y_{dt} is a vector of labor outcomes at destination municipality d in year t, m_{dt} is the destination migrant inflow, X_{dt} are municipality-level controls, ψ_t absorb year fixed effects and ϵ_{dt} is the error term. By differencing the outcome variables we can account for time-invariant unobserved characteristics that could be correlated with migration inflows, but the error term may include unobserved time-varying confounders which would potentially bias OLS estimates. In particular, migrants could choose a specific destination municipality due to demand shocks leading to higher wages or job prospects.

We account for this endogeneity problem following a two-step procedure to construct an instrumental variable for the number of migrants entering a destination. First we predict m_{ot}, the migration outflow rate[21] from origin municipality o in year t, using weather shocks in the previous year:

$$m_{ot} = \alpha + \beta' Z_{ot-1} + \phi_o + \delta_t + \varepsilon_{ot} \tag{3}$$

where Z is a vector of rainfall and temperature shocks at the origin municipality o in the previous year, ϕ_o and δ_t are municipality and year fixed effects, respectively, and ε_{ot} is a random error term. For each year the predicted number of migrants who leave their hometowns is obtained by multiplying this predicted rate by the municipality population reported in the 1991 Census:

$$\widehat{M}_{ot} = \widehat{m}_{ot} \times P_o \tag{4}$$

In the second step we use the past settlements of migrants from the origin o to municipality d in order to distribute them throughout the destination areas by defining our instrument as

$$\widetilde{m}_{dt} = \sum_{o=1}^{O} \frac{s_{od} \times \widehat{M}_{ot}}{P_d} \tag{5}$$

where s_{od} is the share of migrants from origin municipality o who lived in the destination area d in 1991[22] and P_d is total population at d in 1991.[23] Thus our instrument $\widetilde{m}_{dt}$ can be

[21] Defined as the observed number of migrants leaving the municipality divided by the population in the 1991 Census.

[22] We fix our past settlement measure in 1991 across the time span of our sample so as to avoid concerns about the persistence in migrant flows as discussed by Jaeger et al. (2018). We also experimented with an specification that updates past settlement using the data from the immediate previous Census and results are similar.

[23] In appendix B we further discuss our shift-share instrument in more detail.

thought as a combination of exogenous shocks or 'shifts' $\widehat{M}_{ot}$ (weather-driven outflows) and exposure 'shares' ($s_{od} \geq 0$) or past settlement patterns.

The validity of the shift-share instrument approach relies on assumptions about the shocks, exposure shares, or both, as discussed by a recent literature which analyzes its formal structure. Goldsmith-Pinkham et al. (2020) demonstrate that a sufficient condition for consistency of the estimator is the strict exogeneity of the shares. Alternatively, Borusyak et al. (2021) show how one can instead use the exogenous variation of shocks for identification by estimating a transformed but equivalent regression - at the origin level in our setup - where shocks are used directly as an instrument.

Based on these insights, we leverage origin-level weather shocks for identification and define the reduced-form relationship that associates labor market outcomes and the predicted migrant flow at the destination as

$$\Delta y_{dt} = \alpha + \beta \widetilde{m}_{dt} + \gamma \Delta X_{dt} + \psi_t + \epsilon_{dt} \tag{6}$$

which is the main specification we use throughout the paper. As discussed in detail by Borusyak et al. (2021), the consistency of our shift-share approach is based on two conditions:

Assumption 1 (*Quasi-random shock assignment*): $\mathbb{E}[Z_{\tilde{o}}|\bar{e}, s] = \mu$ for all $\tilde{o}$.

Assumption 2 (*Many uncorrelated shocks*): $\mathbb{E}[\sum_o s_o^2] \to 0$ and $Cov[Z_{\tilde{o}}, Z_{\tilde{o}'}|\bar{e}, s] = 0$ for all $\tilde{o}, \tilde{o}'$.

where $\tilde{o} = (o, t)$, $\bar{e} = \{\bar{e}_{\tilde{o}}\}_{\tilde{o}}$, $s_o = \sum_d s_{od}$ and $s = \{s_o\}_o$.[24] Assumption 1 guarantees that our shift-share IV is valid when weather shocks are as-good-as-randomly assigned, which comes from standard natural shocks arguments. Given identification, Assumption 2 gives us consistency when the number of observed shocks is large and when shocks are mutually uncorrelated given the unobservables and s_o. In section 4.2 and Appendix D, we argue that Assumption 2 is satisfied in our setup. Finally, we present evidence regarding our first-stage in section 3.3.

Regarding hypothesis testing, Adao et al. (2019) show that conventional inference in shift-share regressions are generally invalid because observations with similar exposure shares are likely to have correlated residuals, potentially leading to null hypothesis overrejection. In Appendix C, we take advantage of the equivalence result of Borusyak et al. (2021) to show that these inference issues are not empirically relevant in our setup.[25]

[24] As in Borusyak et al. (2021), $\bar{e}_{ot} = \frac{\sum_d P_d s_{od} \epsilon_{dt}}{\sum_d P_d s_{od}}$ correspond to the error term from equation 2 computed at the level of shocks (e.g. municipality of origin).

[25] By estimating shift-share coefficients with a shock-level IV regression, Borusyak et al. (2021) also show that one obtains standard errors that are asymptotically valid regardless of the correlation structure of the error term.

3.3 Weather-induced migration

We begin the exploration of our first-stage results by estimating variations of specification 3 and report the estimates in Table 4. All regressions control for temperature shocks and the log of total population in the previous census; and include time and municipality fixed effects. In columns (2)-(8) we include a flexible trend interacting time dummies with 1991 characteristics (age and the shares of high school and college educated individuals). Columns (3)-(6) include up to three lags, contemporaneous and one lead of rainfall and temperature shocks. For brevity, we omit (mostly insignificant) coefficients associated with temperature shocks in Table 4. Standard errors are clustered at the grid level to account for the fact that municipalities in the same grid will have similar shocks.[26]

As expected, rainfall shocks in the previous year are negatively correlated with migration outflows indicating that Semiarid's inhabitants leave the region during drought periods. Coefficient estimates are remarkably stable across specifications and adding more lags do not change the baseline results. More important to our identification, we include as control rainfall and temperature shocks one year forward to ensure that our instrument is not contaminated by serial correlation in the weather measures. The coefficient on $rainfall_{t+1}$ reported in column (6) is small in magnitude and not statistically significant, while the coefficient for $rainfall_{t-1}$ remains almost unchanged. Our estimates indicate that a municipality where annual rainfall is 10% below historical average will experience an increase of $1p.p.$ in migration outflow rate.

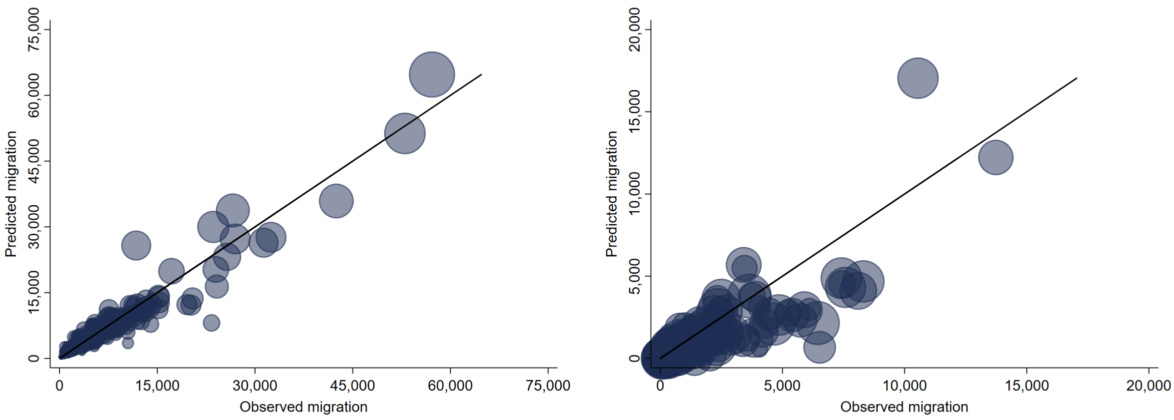
Next, we distribute the predicted migration outflows shock using past settlement patterns of migrants from origin municipality o to destination d. A *sine qua non* requirement implicit in our empirical framework is that both predicted migration inflow and outflow rates, $\widetilde{m}_{ot}$ and $\widetilde{m}_{dt}$ respectively, should be strongly correlated with their observed counterparts. Figure 3 illustrates that our predictions provide a strong fit of the observed migration. Panel (a) shows the relationship between the predicted and observed number of migrants leaving the Semiarid region and entering non-Semiarid municipalities, cumulated over the period 1996-2010. Panel (b) shows the predicted and observed numbers of incoming Semiarid migrants for destination municipalities.

In Appendix B we describe in more detail our data source for weather shocks, discuss alternative measures of weather, and present further details about how we constructed our instrument including predicted and past settlement patterns.

Overall, this analysis shows that our strategy provides a strong first-stage as predicted migration rates, $\widetilde{m}_{dt}$, are strongly correlated with observed migration. For simplicity, as our main results we reports estimates of the effects of predicted migration on labor market outcomes in the next section. In section 4.1 we report the corresponding IV estimates (instrumenting observed migration by predicted migration) for our main findings. In particular, Table 10 reveals that our first-stage point estimates are close to a

[26]Similar, but not equal to, as shocks are computed by taking the average of the grid's four nodes, weighted by the inverse of the distance from each node to the municipality centroid.

Figure 3: Observed vs predicted migration



(a) Migration outflow

(b) Migration inflow

Notes: This figure presents the relationship between the predicted and observed migration flows across Brazilian municipalities from 1996 to 2010. Panel (a) shows the number of migrants leaving the Semiarid region to non-Semiarid municipalities. Panel (b) shows the number of incoming Semiarid migrants for destination municipalities. Circle size represents the municipality's total population in 1991. *Data source*: Census microdata (IBGE).

one-to-one relationship (0.92) - making the magnitude of reduced-form and IV estimates almost identical - and have an F-stat of 220.[27]

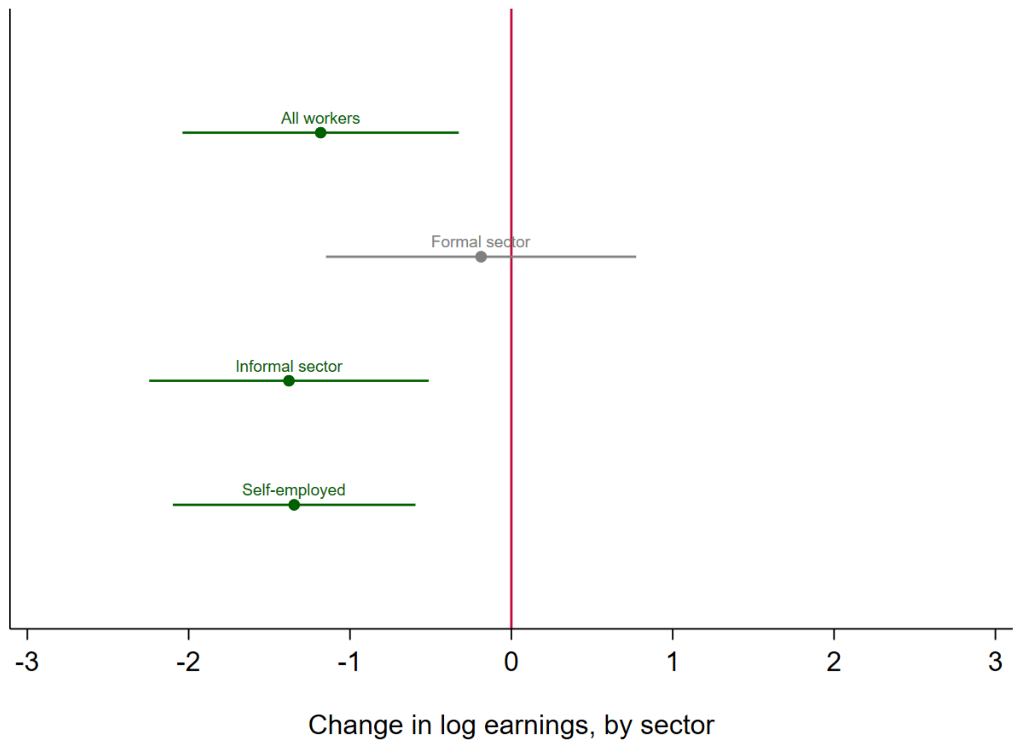
4 Labor Market Effects of Migration Inflows

Now we turn our attention to labor markets at the destination and investigate how internal migration affects earnings, employment and nonwage benefits of native workers.

Effects on earnings. To test the implications of the simple model presented in Section 2.3, we first evaluate whether wages adjust at all in response to the migration flows. Figure 4 summarizes our main findings, while in Table 5 we present the estimates from several specifications for the reduced form equation (6). Column (1) displays a flexible specification, without any control. In column (2) we control for the log of the native population in the previous year and for changes in a set of municipality-level demographics (the share of individuals with high school and college education; the share of female, white and black individuals; and a cubic polynomial of age). Column (3) also controls for these changes in demographics and includes time dummies. Finally, there are two important changes occurring during our period that could be a concern for our identification: population aging and an increase in education levels. To account

[27]A sufficiently high F-stat avoids weak instrument concerns, especially in the light of the recent discussion in Lee et al. (2020) who show that a 5 percent test requires a F statistic of 104.7, significantly higher than the broadly accepted threshold of 10.

Figure 4: **Effects of predicted migration on earnings**



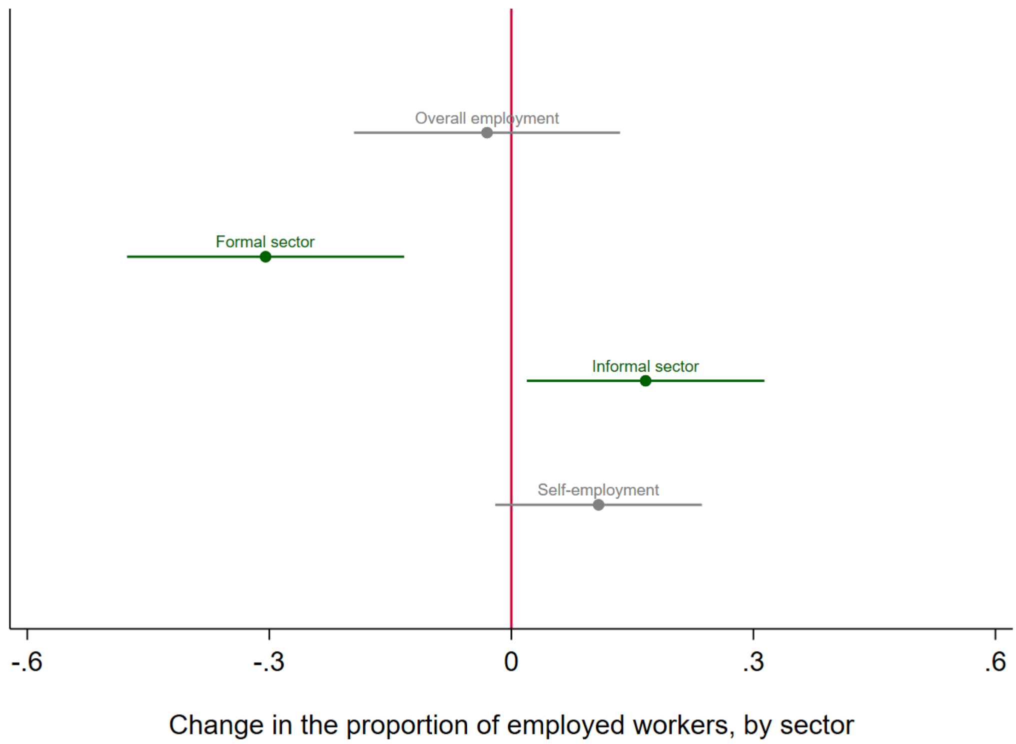
Notes: This figure plots regression coefficients of change in log earnings, by sector, against the predicted number of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. Controls include time dummies, the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Standard errors are clustered at the municipality level. Green markers are statistically significant at the 5% level.

for this, in Column (4) we include a linear trend of age and the shares of high school and college educated individuals. All regressions are weighted by the 1991 native population to account for the fact that heterogeneity in municipality size could lead to differential effects.

Panel A reveals a strong negative effect of the predicted inflow of migrants on average log earnings for native workers. The inclusion of controls diminishes a little the magnitude of our coefficient of interest, but that does not change substantially our main conclusion. One percentage point increase in the predicted number of migrants reduces earnings by 1.3%. In Panel B we restricted our analysis to native workers holding a formal job, while in Panels C and D we focus on those in the informal sector and self-employed, respectively. There is no significant effect on the earnings of formal workers, but for those individuals in the informal sector and self-employed earnings are reduced by 1.5% and 1.4%, respectively.

Any downward wage restrictions such as minimum wages or collective bargaining agreements may prevent wages from falling in the formal sector. This explains the negative however small and insignificant effect of migration on formal sector wages.

Figure 5: **Effects of predicted migration on employment**



Notes: This figure plots regression coefficients of change in employment rate, by sector, against the predicted number of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. Controls include time dummies, the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Standard errors are clustered at the municipality level. Green markers are statistically significant at the 5% level.

However, in the informal sector, the large negative impact on wages is consistent with absence of downward wage rigidity in this sector such that the classic predictions from perfect competition prevail. Regarding self-employment, if the demand in the product market is fixed, there is more competition faced by native self-employed workers therefore the supply shock due to migration causes earnings to fall.

Effects on employment. Our wage results imply that it is more expensive to hire workers in the formal than in the informal sector. If the informal sector and self-employment absorbs all workforce who left the formal sector, we should not expect impacts on total employment. Figure 5 summarizes our main employment results, while in Table 6 we present the point estimates in detail.

As we see, there is a small negative but insignificant effect on overall employment, however predicted migration does affect the composition of workers across sectors. Our estimates in Panels B to D imply that one percentage point increase in the predicted inflow reduces the share of formal employment by $0.3p.p.$, and increases the share of informal workers and those in self-employment by $0.15p.p.$ and $0.10p.p.$, respectively.

Most of these estimates are precise and stable across specifications.

The results by sector are consistent with the two versions of the model we presented in Section 2.3. When the labor market in a receiving municipality is hit by a supply shock, native workers face more competition. In a simple competitive labor market setting with elastic labor supply, employment of natives is expected to reduce. When we introduce downward wage constraints in the model, in absence of any other margin of adjustment, then employment may further reduce. This explains the negative impact on formal employment.

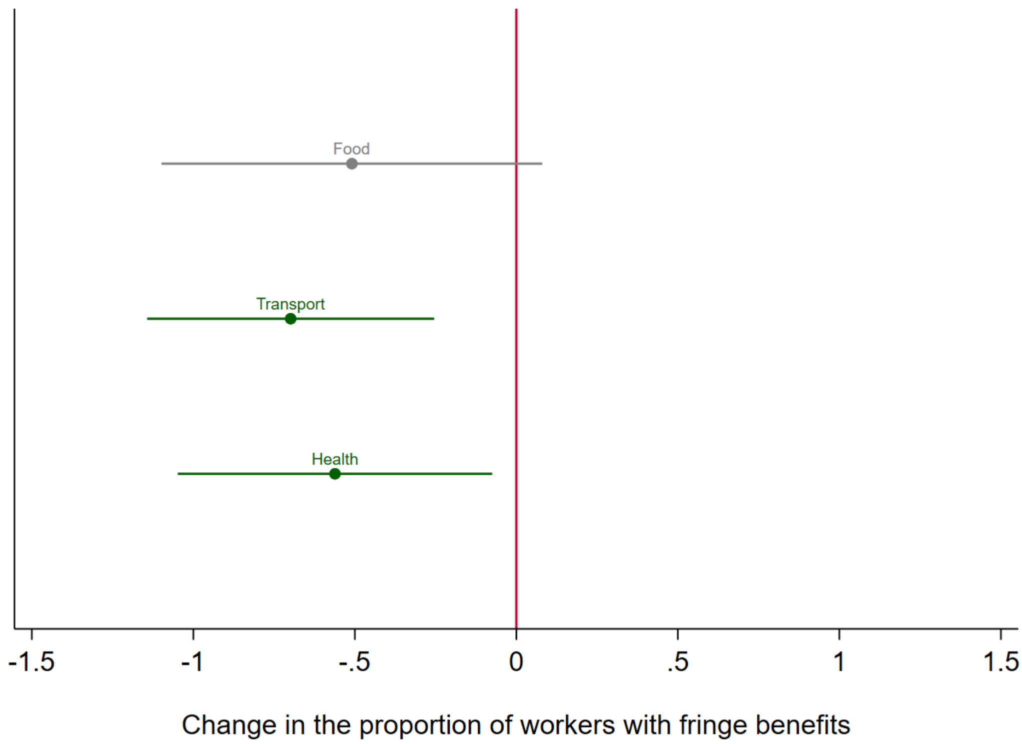
On the other hand, the share of native workers in the informal sector and self-employment rise consistently with the existence of a dual labor market, with an unregulated sector, where the minimum wage and other labor laws do not apply.

Effects on nonwage compensation. Our paper exploits an additional important margin of adjustment due to migration shocks. Because firms operating in the formal sector cannot reduce wages below the legal minimum they may adjust to labor supply shocks by reducing their fringe benefits offerings. We focus on individuals who are currently holding a formal job because these benefits are almost exclusively offered by formal firms. Figure 6 presents the main results for this mechanism. Corresponding estimates are provided in Table 7. Although in this case the results are more sensitive to the specification, all point estimates are negative and suggest an important effect. We find that a one percentage point increase in the predicted number of migrants reduces the share of workers receiving health insurance in the range of $0.2p.p.$ to $0.6p.p.$, transport from $0.5p.p.$ to $0.7p.p.$, and food subsidy from $0.3p.p.$ to $0.7p.p.$.

In summary, the model we presented in Section 2.3 generates predictions broadly consistent with our findings. In the formal sector, we observe no change in earnings, a decline in nonwage job benefits, and a decrease in employment of natives, which occurs due to wage rigidity and an imperfect adjustment of the benefit margin. In the informal sector and self-employment, where the minimum wage does not apply, we find a decrease in earnings. We also find an increase instead of a decrease in employment, consistent with workers reallocating from the formal to the informal sector or self-employment.

Effects on unemployment and labor force participation. Finally, to draw a more complete picture we also look at the impacts on unemployment and labor force participation. In Panel A from Table 8 the dependent variable is the change in the municipality-level proportion of unemployed native workers. We observe that migration inflows lead to an increase in the unemployment rate ($0.16p.p.$). In Panel B, the outcome is the change in the proportion of individuals out of the labor force and the point estimate is almost identical, even though with opposite sign. But, in this case is hard to tell ex-ante what should be the most likely effect. On one hand, increased competition in the labor market could discourage native individuals to work if wages or benefits fall down. On the other hand, if the primary earner in the household looses his/her job because of the

Figure 6: **Effects of predicted migration on nonwage compensation**



Notes: This figure plots regression coefficients of change in the proportions of formal sector workers who receive health insurance, food or transport subsidies against the predicted number of migrants from the Semiarid region in each destination municipality (measured as a fraction of the native working-age population in 1991). Controls include time dummies, the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Standard errors are clustered at the municipality level. Green markers are statistically significant at the 5% level.

increased competition, then it is possible that other members of the household would enter the market, a phenomenon known as the added worker effect (Lundberg, 1985). We test this second mechanism running the same regressions separately for individuals identified as head or non-head of the household. As we can see in Table 9, almost all the impact on the employment margins comes from those native workers who are head of the household, while the change in unemployment and inactivity rates are led by the non-head members. This confirms our intuition that the second channel prevails. Also, the symmetry between the effects on unemployment and inactivity suggests that once secondary earners enter the market, it takes time for them to actually find a job.

Differential effects along the earnings distribution. We also investigate the existence of differential effects according to the native worker's position in the earnings distribution and present the estimates in Figure 7. We estimate the reduced form on each decile of earnings, by sector. For those native workers employed in the formal sector, there is no statistically significant effect along the entire distribution. Benefits' adjustment can help explaining why we find null effects on formal sector wages across the entire wage distribution and not only on bottom wages which is explained through minimum wages.

For informal and self-employed workers, the impact is substantially stronger for those at the bottom third of both distributions, consistent with classic predictions from perfect competitition and greater substitutability between migrants and less skilled natives in these sectors. To a smaller extent, migration also affects higher earnings deciles of informal sector workers and self-employed. The negative impact of migration in this case is attenuated due to some formal sector workers moving into informality or self-employment. As workers in the formal sector are more productive, on average, this increases earnings at higher percentiles in other sectors.

4.1 IV Estimates

In this section we present the two-stage least squares (2SLS) estimates of the parameters of interest using the predicted migration rate as an instrument for the observed inflow. In Table 10 we report OLS estimates in columns (1), (3), (5) and (7) and IV estimates in columns (2), (4), (6) and (8), as well as the associated first-stage coefficients and F-statistics. All regressions are weighted by the total native population in 1991 and include time and state dummies, as well as demographic controls. Standard errors were calculated via bootstrapping to account for the fact that our instrumental variable was created with an estimated shock.

As illustrated by Figure 3 and briefly discussed in the end of Section 3.3, Table 10 shows that our first-stage point estimates are close to a one-to-one relationship (0.92) - making the magnitude of IV and reduced-form estimates (reported in Table 6) almost identical. A F-stat of 220 avoids weak instrument concerns, especially in the light of the recent discussion in Lee et al. (2020).

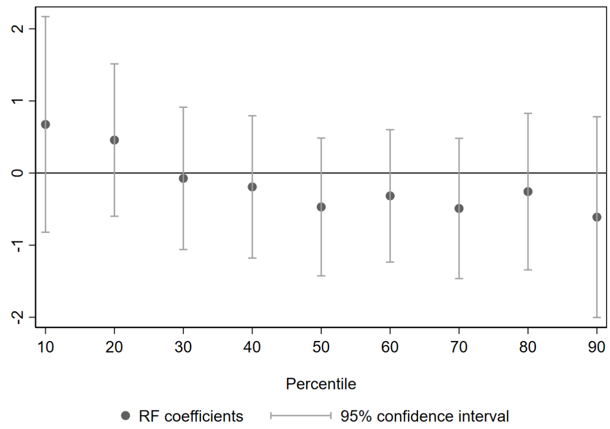
At a first glance, it is not clear what to expect from the direction of the OLS bias in our setup. On the one hand, one could expect that migrants moving into booming municipalities would lead OLS estimates to be biased upwards. On the other hand, attenuation bias could dominate if classical measurement error is relevant in observed migration. Indeed, coefficients in Tables 10 show that OLS estimates are biased toward zero across most specifications across formal, informal and self-employment workers. The same is true for the estimates on labor force participation reported in Table 11, but not for unemployment.

4.2 Sensitivity checks

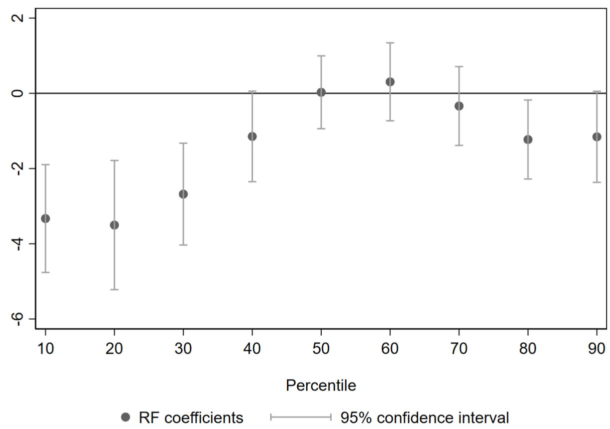
Now we summarize a series of robustness checks we have performed to assess the validity of our main findings.

The first issue we address is whether a shift in local labor demand may be confounding our identification. If that was the case, then we should expect that migrants from other regions outside the Semiarid would be attracted for the same destinations. In other words, we should observe a positive correlation between migrant inflows from

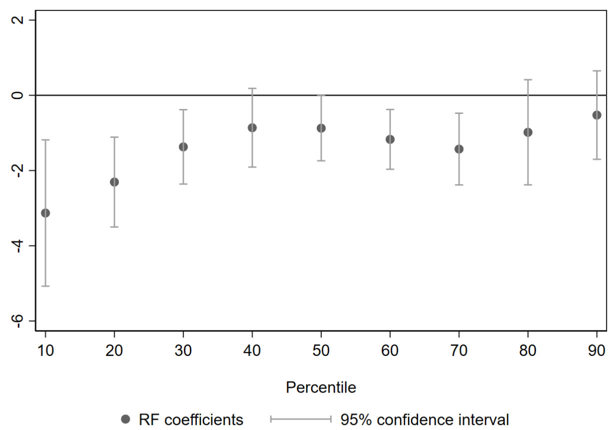
Figure 7: Effects of predicted migration along the earnings distribution



(a) Formal sector



(b) Informal sector



(c) Self-employment

Notes: This figure plots regression coefficients of change in the average of log earnings, in each decile, against the predicted number of migrants from the Semiarid, measured as a fraction of the native working-age population in 1991. Panels (a), (b) and (c) restrict the sample to individuals in the formal sector, informal sector and self-employment, respectively. Controls include time dummies, the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. The capped lines show the 95% confidence interval. Standard errors are clustered at the municipality level.

the Semiarid and that from other regions. In Table 12 we show the coefficients from a regression of the migration inflow rate of migrants from other regions on our instrument. Column (1) includes time and municipality fixed effects. In Column (2) we add the same set of controls from our main results and Column (3) also includes the same linear trends as before. There is no statistically significant impacts in any specification.

The second issue is that our strategy relies on the assumption that rainfall at origin municipalities affects destination labor markets only through internal migration. One possible violation of this assumption would be if a negative income shock at the origin, due to low rainfall levels, had reduced trade flows with some of the destination areas, for instance. In this case, one should expect higher effects in those industries more exposed to trade shocks, like agricultural or manufactured goods. In Table 13 we report the coefficients from a regression of the predicted inflow rate on changes in log earnings by industry. Panel A and B show the effects on native workers employed in the agricultural and manufacturing sector, respectively. In both cases, although the coefficients display a negative sign, they are not significant. In contrast, in Panel C we show that the effect on those employed in services have larger magnitude and are statistically significant across all colums.

Next, in Appendix C we address the issue raised by Adao et al. (2019) who argue that the typical shift-share design standard errors may be underestimated because as regression residuals are by design correlated across units with similar shares. By reestimating our regressions at the origin/shock level as suggested by Borusyak et al. (2021), we show that the shock-level standard errors are similar to the ones reported in our main tables, suggesting that these inference issues are not empirically relevant in our setup.

Finally, we explore the sensitivity of our results according to the degree of aggregation of regions of origin. According to Assumption 2, the consistency of our shift-share instrument needs origin-level shocks to be mutually uncorrelated. As rainfall shocks are likely correlated across smaller geographical units, in Appendix D we investigate this issue by re-constructing our instrument according to larger catchment areas of origin of a migrant - such as a microregion or mesoregion - instead of a municipality.[28] First, we document that spatial autocorrelation among shocks decrease dramatically as we consider larger areas. Second, Tables D2-D5 show that our results associating migration and rainfall, earnings, employment and nonwage benefits remain virtually unchanged, indicating that spatial autocorrelation among rainfall shocks in origin municipalities are irrelevant our results.

[28]IBGE (1990) defines microregions as "groups of economically integrated municipalities sharing borders and structure of production". Mesoregions are collections of microregions of which not all municipalities share borders. The Semiarid has 960 municipalities, 137 micro and 35 mesoregions.

5 Differential Effects according to Education

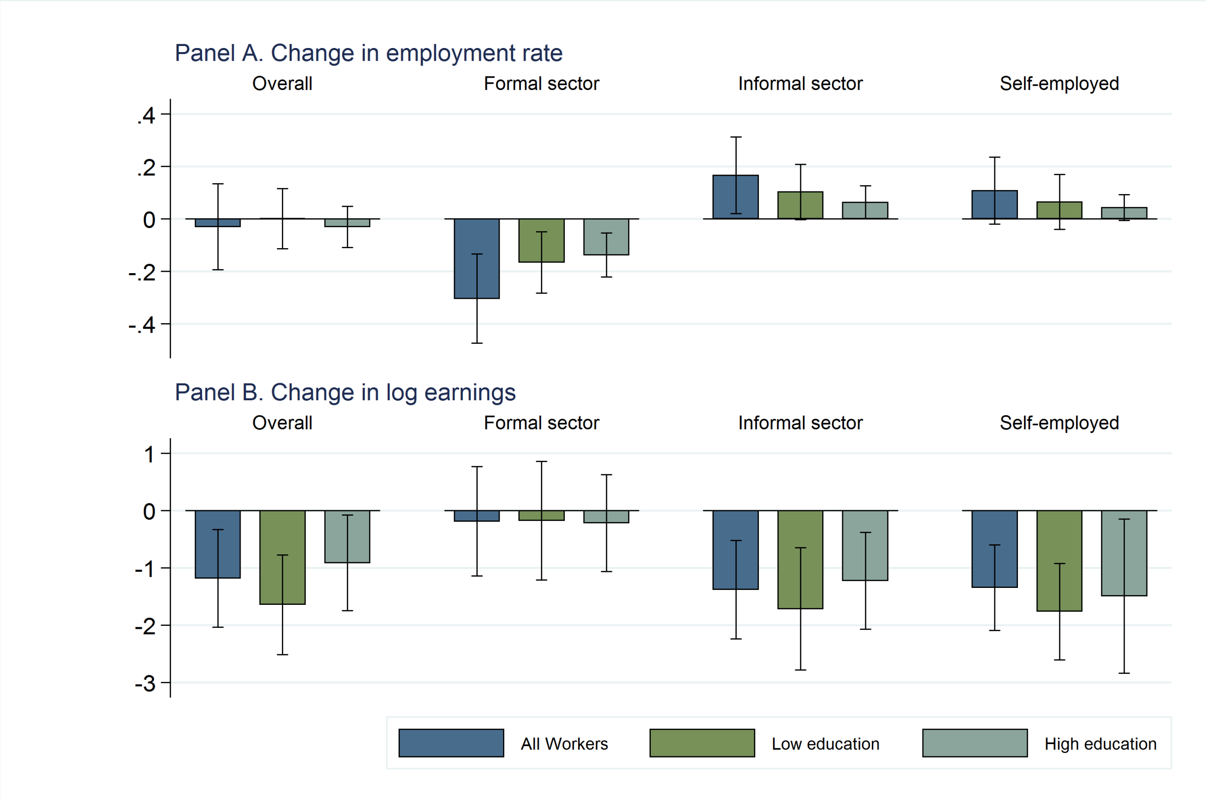
The results reported so far represent estimates of the impact of an exogenous increase in the inflow of migrants from the Semiarid on natives, on average. In this section, we consider the case in which individuals with different levels of education may experience different effects. In particular, we expect that native workers whose skill level are similar to migrants, i.e. those with low education, to be close substitutes. Thus we reestimate the effect of migration on local labor market outcomes of natives with low and high education, separately. We define as low educated those with up to 7 years of schooling, which is equivalent to an incomplete elementary education. In our sample, 59% of natives are less educated.

Figure 8 illustrates the estimates by education. Panel A shows the effect of predicted migration on the changes in employment rates, by sector and education group. Low-educated native individuals are more likely to exit the formal sector and to become informal sector workers compared to those who have higher education. In Panel B we analyze the differential effects on log earnings. In the formal sector, there is no significant impact on native workers across education levels. This is again consistent wage rigidity due to minimum wages or contractual wages preventing downward adjustments in the formal sector. On the other hand, native workers with low education have a relatively higher loss in informal and self-employment earnings, consistent with the conjecture that they compete more directly with (low-skilled) migrants.

In terms of adjustments on the nonwage benefits margin, it is less clear why they should differ by worker skills. In principle, working in the same firm implies that workers of different skills are offered a common benefits package. However, if there is a positive matching in the labor market with low (high) education workers selecting into less (more) productive and small (large) firms, then we should expect the less educated workers to be the most affected as the minimum wages bind more tightly in the firms where they work. In Figure 9 we show that the negative impact on food and transport benefits are indeed stronger and relatively more precise for low education workers. In contrast, high education workers have a clear reduction in employer-provided health insurance which is consistent again with some selection of these workers in large firms which tend to offer health insurance and where there is a mix of high and some low education workforce. A possible explanation is that the inflow of migrants competing with native low education workers in large firms pressures wages down. However under minimum wage restrictions, the adjustment occurs through lowering health insurance.

Changes in the benefits can have important welfare implications. We found that migration lowers the provision of food and transport benefits to less educated individuals. On the other hand, we show that health insurance is not significantly changed for low education workers on average, while it is less offered for the high education workers. Considering that food and transport are the two most offered benefits in the data (as shown in Table 2) and to the extent that workers value these benefits, their

Figure 8: **Effects of migration on employment and earnings, by education level**



Notes: This figure plots regression coefficients of change in labor market outcomes, by education level, against the predicted number of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. In Panel A, the dependent variables are the changes in employment rates while in Panel B we present estimates for changes in log earnings, for each sector. Each bar represents the reduced form coefficient for the average and by education (low education = up to 7 years of schooling). All regressions are weighted by total native population in 1991, include time dummies and control for the log of native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. The capped lines show the 95% confidence intervals.

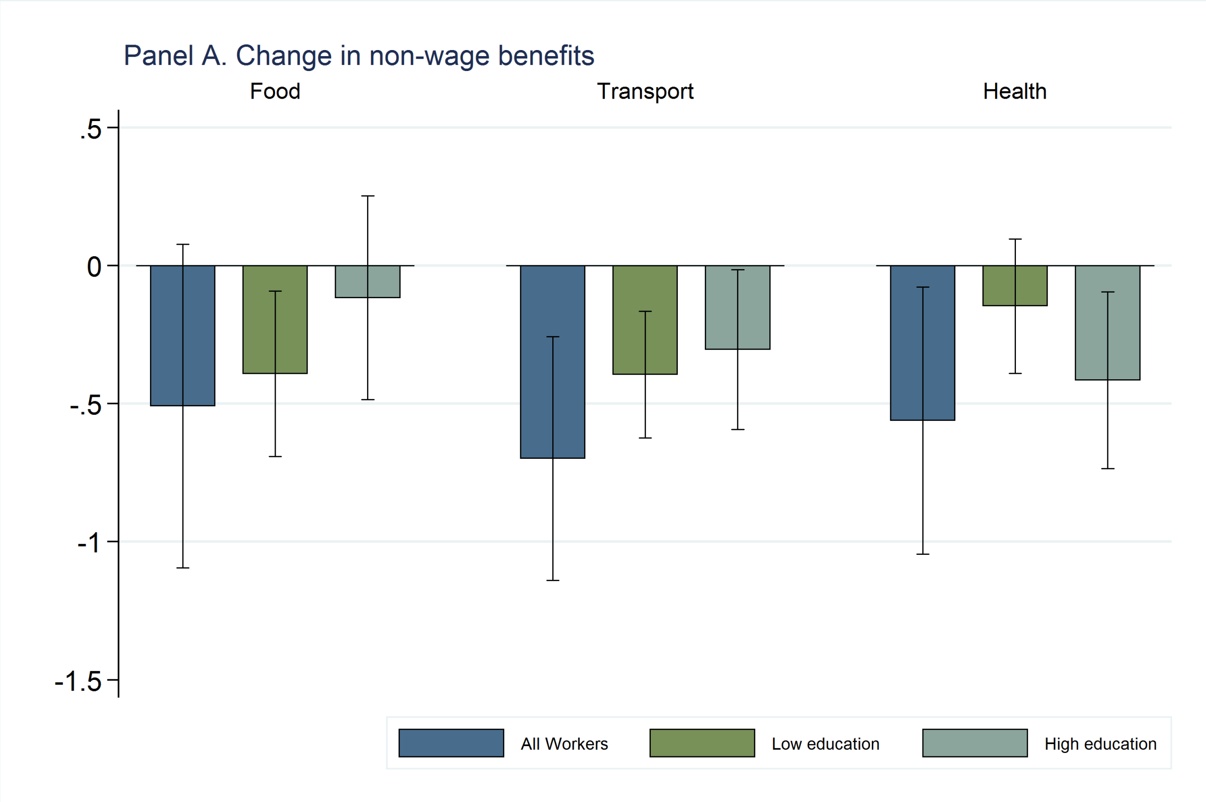
reduction together with a stronger negative impact on earnings for the low education workers suggest that the welfare of the less educated workers declines more than for high education workers.

6 Conclusion

In this paper we investigate the labor market impacts of weather-induced internal migration in Brazil. We use a shift-share instrument approach combining variation in the number of people leaving their hometowns, driven by weather shocks, with past settlement patterns to exploit exogenous variation in the number of migrants entering each destination municipality.

We find that internal migration reduces formal employment and raises the share of informal sector workers and self-employed. We also find a reduction in earnings

Figure 9: **Effects of predicted migration on nonwage benefits, by education level**



Notes: This figure plots regression coefficients of change in nonwage benefits, by education level, against the predicted number of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. The dependent variables are the changes in the proportions of native workers in the formal sector who received some help to cover expenses with food, transport or health insurance. Each bar represents the reduced form coefficient by education level (low education = up to 7 years of schooling). All regressions are weighted by total native population in 1991, include time dummies and control for the log of native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. The capped lines show the 95% confidence intervals.

for natives in the informal sector or self-employed, but no effect on formal workers. For them, adjustment occurs through reductions in nonwage benefits such as health insurance, food and transport subsidies. As a result, there is no change in overall employment. This is consistent with workers reallocating to the informal sector or self-employment as well as adjustments in wage and nonwage benefit margins. Most effects are stronger for low educated individuals, which are more likely to be substituted by migrants escaping droughts. In particular, evidence that internal migration reduces informal sector earnings and nonwage job benefits more strongly for low education workers suggest that welfare inequality among natives rises.

References

Adao, R., M. Kolesár, and E. Morales (2019). Shift-share designs: Theory and inference. *The Quarterly Journal of Economics 134*(4), 1949–2010.

Almeida, R. and P. Carneiro (2012, July). Enforcement of labor regulation and informality. *American Economic Journal: Applied Economics 4*(3), 64–89.

Altonji, J. G. and D. Card (1991). The effects of immigration on the labor market outcomes of less-skilled natives. In *Immigration, trade, and the labor market*, pp. 201–234. University of Chicago Press.

ANS (2018). Painel de precificação: Planos de saúde. Agência Nacional de Saúde Suplementar, http://www.ans.gov.br/materiais-publicados/periodicos.

ANS (2019). Dados e indicadores do setor. Agência Nacional de Saúde Suplementar, http://www.ans.gov.br/perfil-do-setor/dados-e-indicadores-do-setor. Last accessed on 28/10/2020.

Arbache, J. S. (1995). Uma introdução aos salários indiretos no brasil. Anais, Encontro Nacional de Estudos do Trabalho, São Paulo. p. 1297-1322.

Arbache, J. S. and D. M. Ferreira (2001). Salários indiretos e previdência social no brasil. *Estudos Empresariais 6*(1), 37–44.

Assunção, J. and F. Chein (2016). Climate change and agricultural productivity in brazil: future perspectives. *Environment and Development Economics 21*(5), 581–602.

Babecký, J., C. Berson, L. Fadejeva, A. Lamo, P. Marotzke, F. Martins, and P. Strzelecki (2019). Non-base wage components as a source of wage adaptability to shocks: evidence from european firms, 2010–2013. *IZA Journal of Labor Policy 8*(1), 1.

Babecký, J., P. Du Caju, T. Kosma, M. Lawless, J. Messina, and T. Rõõm (2012). How do european firms adjust their labour costs when nominal wages are rigid? *Labour Economics 19*(5), 792–801. Special Section on: Price, Wage and Employment Adjustments in 2007-2008 and Some Inferences for the Current European Crisis.

Barbieri, A. F., E. Domingues, B. L. Queiroz, R. M. Ruiz, J. I. Rigotti, J. A. M. Carvalho, and M. F. Resende (2010). Climate change and population migration in brazil's northeast: scenarios for 2025–205. *Population and Environment 31*, 344–370.

Beenstock, M., D. Felsenstein, et al. (2019). *The econometric analysis of non-stationary spatial panel data*. Springer.

Borjas, G. J. (2003). The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market. *The Quarterly Journal of Economics 118*(4), 1335–1374.

Borjas, G. J. (2014). *Immigration Economics*. Cambridge: Harvard University Press.

Borjas, G. J. and J. Monras (2017). The labour market consequences of refugee supply shocks. *Economic Policy 32*, 361—-413.

Borusyak, K., P. Hull, and X. Jaravel (2021). Quasi-experimental shift-share research designs. *The Review of Economic Studies*, Forthcoming.

Boustan, L. P., P. V. Fishback, and S. Kantor (2010). The effect of internal migration on local labor markets: American cities during the great depression. *Journal of Labor Economics 28*(4), 719–746.

Busso, M., J. P. Chauvin, and N. Herrera L (2021). Rural-urban migration at high urbanization levels. *Regional Science and Urban Economics*, forthcoming.

Carabetta, J., R. H. M. Pereira, and C. N. Goncalves (2020). geobr: Loads shapefiles of official spatial data sets of brazil. python package version 0.1.5. *The Python Package Index (PyPI)*.

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics 19*(1), 22–64.

Card, D. (2009, May). Immigration and inequality. *American Economic Review 99*(2), 1–21.

Card, D. and G. Peri (2016). Immigration Economics by George J. Borjas: A Review Essay. *Journal of Economic Literature 54*(4), 1333–49.

Cardoso, A. and T. Lage (2006). Labor inspection in Brazil. *Dados 2*, Rio de Janeiro.

Cardoso, A. and P. Portugal (2005). Contractual wages and the wage cushion under different bargaining settings. *Journal of Labor Economics 23*(4), 875–902.

Carvalho, J. A. and R. A. Garcia (2002). Estimativas decenais e quinquenais de saldos migratorios e taxas líquidas de migração do brasil. Working paper, Cedeplar/UFMG.

Cattaneo, C., C. V. Fiorio, and G. Peri (2015). What happens to the careers of european workers when immigrants "take their jobs"? *Journal of Human Resources 50*(3), 655–693.

Cavalcanti, F. (2018, March). Voters sometimes provide the wrong incentives. The lesson of the Brazilian drought industry. MPRA Paper 88317, University Library of Munich, Germany.

Clemens, J. (2021, February). How do firms respond to minimum wage increases? understanding the relevance of non-employment margins. *Journal of Economic Perspectives 35*(1), 51–72.

Clemens, J., L. B. Kahn, and J. Meer (2018, May). The minimum wage, fringe benefits, and worker welfare. Working Paper 24635, National Bureau of Economic Research.

Corbi, R., R. Ferreira, R. Narita, and D. Souza (2021). Labor courts, job search and employment: Evidence from a labor reform in brazil. Working paper, University of Sao Paulo.

Correia, S. (2017). Linear models with high-dimensional fixed effects: An efficient and feasible estimator. Working paper. http://scorreia.com/research/hdfe.pdf.

Dustmann, C., T. Frattini, and I. P. Preston (2012). The effect of immigration along the distribution of wages. *Review of Economic Studies 80*(1), 145–173.

Dustmann, C. and A. Glitz (2015). How do industries and firms respond to changes in local labor supply? *Journal of Labor Economics 33*(3), 711–50.

Dustmann, C., U. Schönberg, and J. Stuhler (2016). The impact of immigration: Why do studies reach such different results? *The Journal of Economic Perspectives 30*(4), 31–56.

Foged, M. and G. Peri (2016). Immigrants' effect on native workers: New analysis on longitudinal data. *American Economic Journal: Applied Economics 8*(2), 1–34.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2020, August). Bartik instruments: What, when, why, and how. *American Economic Review 110*(8), 2586–2624.

Gonzaga, G. (2003). Labor turnover and labor legislation in Brazil. *Economía (Journal of the Latin American and Caribbean Economic Association) 4*(1), 165–222.

Harris, I., T. J. Osborn, P. Jones, and D. Lister (2020). Version 4 of the cru ts monthly high-resolution gridded multivariate climate dataset. *Scientific data 7*(1), 1–18.

Harris, J. R. and M. P. Todaro (1970). Migration, unemployment and development: A two-sector analysis. *American Economic Review 60*(1), 126–142.

Hornbeck, R. (2012). The enduring impact of the american dust bowl: Short-and long-run adjustments to environmental catastrophe. *American Economic Review 102*(4), 1477–1507.

Jaeger, D. A., J. Ruist, and J. Stuhler (2018, February). Shift-Share Instruments and the Impact of Immigration. Working Paper 24285, National Bureau of Economic Research.

Kahn, A. S. and R. T. Campus (1992). Effects of drought on agricultural sector of northeast brazil. Working paper.

Kleemans, M. and J. Magruder (2018). Labour market responses to immigration: Evidence from internal migration driven by weather shocks. *The Economic Journal 128*(613), 2032–2065.

Lagakos, D. (2020, August). Urban-rural gaps in the developing world: Does internal migration offer opportunities? *Journal of Economic Perspectives 34*(3), 174–92.

Lagos, L. (2020). Labor market institutions and the composition of firm compensation: Evidence from brazilian collective bargaining. Working paper, Columbia University.

Lee, D. S., J. McCrary, M. J. Moreira, and J. Porter (2020). Valid t-ratio inference for iv. Papers, arXiv.org.

Lewis, E. (2011). Immigration, skill mix, and capital skill complementarity. *Quarterly Journal of Economics 126*(2), 1029–69.

Lundberg, S. (1985). The added worker effect. *Journal of Labor Economics 3*(1), 11–37.

Marinho, C. R. V. (2020). Essays on health economics. PhD Dissertation, Insper.

McKenzie, R. (1980). The labor market effects of minimum wage laws: A new perspective. *Journal of Labor Research 1*, 255–264.

Meghir, C., R. Narita, and J.-M. Robin (2015, April). Wages and informality in developing countries. *American Economic Review 105*(4), 1509–46.

Molloy, R., C. L. Smith, and A. Wozniak (2011, September). Internal migration in the united states. *Journal of Economic Perspectives 25*(3), 173–96.

Munshi, K. (2003). Networks in the modern economy: Mexican migrants in the us labor market. *The Quarterly Journal of Economics 118*(2), 549–599.

Narita, R. (2020). Self-employment in developing countries: A search-equilibrium approach. *Review of Economic Dynamics 35*, 1–34.

Ottaviano, G. I. and G. Peri (2012). Rethinking the effect of immigration on wages. *Journal of the European Economic Association 10*(1), 152–197.

Ottaviano, G. I., G. Peri, and G. C. Wright (2013). Immigration, offshoring, and american jobs. *American Economic Review 103*(5), 1925–59.

Perry, G., W. Maloney, O. Arias, P. Fajnzylber, A. Mason, and J. Saavedra-Chanduvi (2007). *Informality: Exit or Exclusion*. Washington, DC: World Bank.

Rocha, R. and R. R. Soares (2015). Water scarcity and birth outcomes in the brazilian semiarid. *Journal of Development Economics 112*, 72–91.

Skoufias, E., K. Vinha, and H. Conroy (2013). The impacts of climate variability on household welfare in rural mexico. *Population and Environment 34*(3), 370–399.

Ulyssea, G. (2020). Informality: Causes and consequences for development. *Annual Review of Economics 12*(1), 525–546.

UN DESA (2017). International migration report 2017. United Nations Department of Economic and Social Affairs, Population Division.

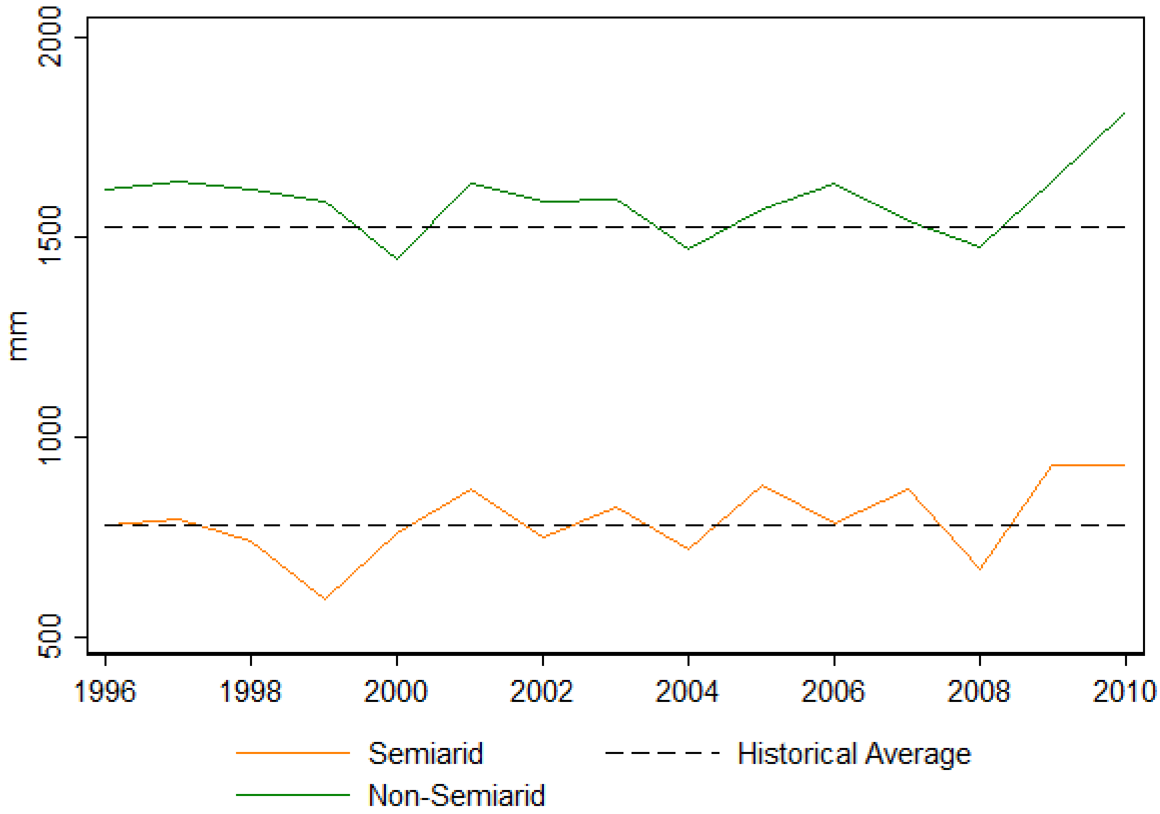
UNDP (2009). Overcoming barriers: Human mobility and development. United Nations Development Program, Human Development Report 2009. http://hdr.undp.org/en/content/human-development-report-2009. Last accessed on 03/09/2021.

Wang, X., A. S. Auler, R. L. Edwards, H. Cheng, P. S. Cristalli, P. L. Smart, D. A. Richards, and C.-C. Shen (2004). Wet periods in northeastern brazil over the past 210 kyr linked to distant climate anomalies. *Nature 432*, 740–743.

Xavier, A. C., C. W. King, and B. R. Scanlon (2016). Daily gridded meteorological variables in brazil (1980–2013). *International Journal of Climatology 36*(6), 2644–2659.

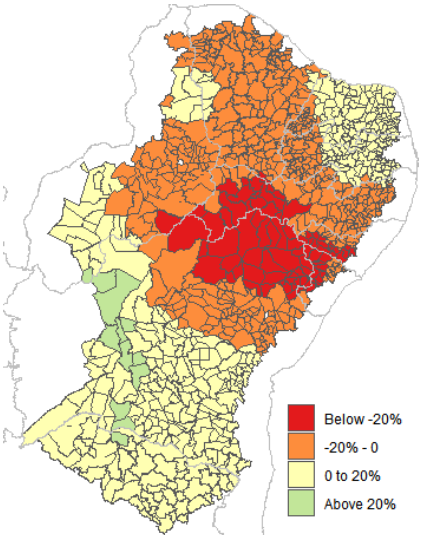
Figures and tables

Figure 10: **Precipitation level: Semiarid vs Non-Semiarid**

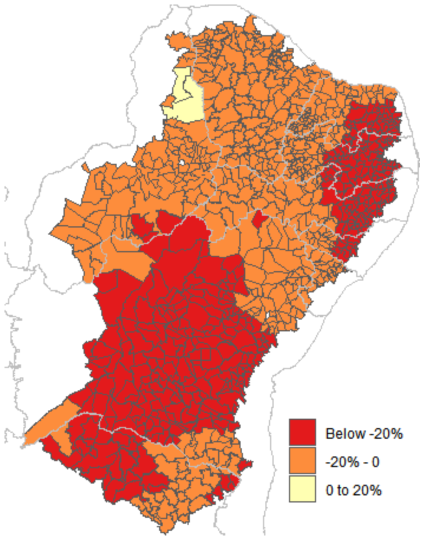


Notes: This figure compares the average precipitation level for the Semiarid region and the rest of the country, from 1996 to 2010. *Data source*: CRU Time Series v4 (Harris et al., 2020).

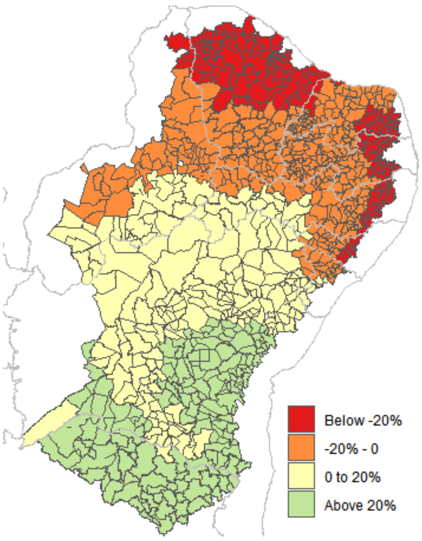
Figure 11: Precipitation levels in the Semiarid region for selected years



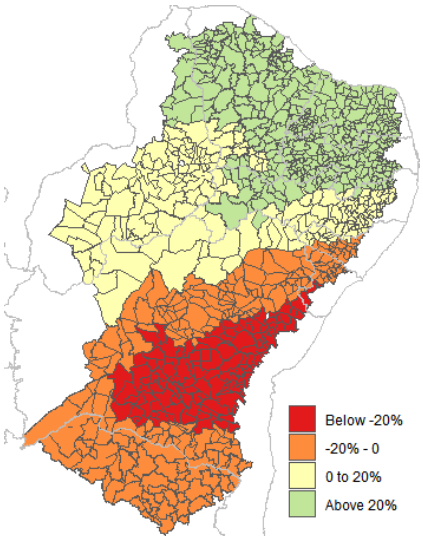
(a) 1997



(b) 2001



(c) 2005



(d) 2009

Notes: This figure presents the distribution of rainfall across the Semiarid region municipalities for selected years. Rainfall is measured as the log-deviations from historical averages. *Data source*: CRU Time Series v4 (Harris et al., 2020).

Table 1: **Summary statistics: weather and migration data**

Panel A: Origin (Semiarid)	Mean	Std. Dev.	Min	Max	Obs
Annual Rainfall	791.09	213.80	266.31	2,028.77	14,400
Rainfall shock	-0.02	0.19	-0.73	0.48	14,400
Annual Temperature	25.54	1.39	21.42	28.93	14,400
Temperature shock	0.01	0.01	-0.01	0.05	14,400
Out-migration	214.16	323.66	0.00	5,773	14,400
Out-migration rate (p.p.)	1.05	0.62	0.00	7.22	14,400
Population	21,260	30,092	1,265	480,949	14,400
Panel B: Destination (Non-Semiarid)	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**
Annual Rainfall	1,610.44	401.69	660.63	3,618.55	8,190
Annual Temperature	23.15	2.82	15.82	28.77	8,190
In-migration	146.69	896.95	0.00	25,423	8,190
In-migration rate (p.p.)	0.27	0.90	0.00	24.30	8,190
Native population	56,382	248,912	312.42	5,113,798	8,190

Notes: Rainfall is measured in mm. Temperature is measured in degrees Celsius. Migration outflow (inflow) rate are the share of migrants over local (native) population.

Table 2: **Summary statistics:**
Native individuals in destination municipalities

	Individual Characteristics				
	Mean	Std. Dev.	Min	Max	Obs
Female	51.08	3.64	0	72.72	8,190
Black	6.23	5.98	0	53.85	8,190
Mulatto	40.32	24.48	0	100	8,190
White	52.82	25.47	0	100	8,190
Age	37.45	1.96	30.15	55	8,190
Years of schooling	6.58	1.78	0	13.52	8,190
Less than elementary	65.32	15.74	4.71	100	8,190
	Employment				
	Mean	Std. Dev.	Min	Max	Obs
Any Employment	62.72	7.95	10	100	8,190
Formal sector	31.34	11.85	0	100	8,190
Informal sector	15.84	6.49	0	64.7	8,190
Self-employed	15.54	6.50	0	71.93	8,190
Unemployed	13.05	7.73	0	80	8,190
Out of labor force	24.23	7.08	0	58.14	8,190
	Earnings				
	Mean	Std. Dev.	Min	Max	Obs
Any Employment	637.87	349.00	60.88	3,582.08	8,190
Formal sector	788.18	439.50	58.67	15,167.10	8,174
Informal sector	382.31	238.34	20	6,000.00	8,172
Self-employed	600.83	385.11	20	6,384.64	8,155
	Nonwage benefits				
Food	38.89	21.06	0	100	8,165
Transport	36.39	25.40	0	100	8,165
Health	20.86	16.41	0	100	8,165

Notes: Each observation is a municipality-year cell. Earnings are measured in R$ of 2012. Nonwage benefits are calculated only for native workers employed in the formal sector.

Table 3: **Comparative characteristics: Migrants vs Natives**

	Migrants		***Low-ed. natives***		***High-ed. natives***	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Age	29.19	10.25	38.43	13.30	33.04	11.14
Number of children	2.13	2.98	3.31	3.07	1.39	1.58
Schooling	4.65	3.96	3.25	2.14	10.90	2.52
Earnings	765.89	1,370.52	783.83	1,516.89	1,994.34	3,300.81
Work less than 40 hours/week	0.11	0.31	0.14	0.34	0.21	0.41
Share of employment	0.67	0.47	0.56	0.50	0.71	0.46
Share of formal employment	0.64	0.48	0.60	0.49	0.81	0.39

Notes: This table compares the characteristics of migrants from the Semiarid region and native individuals in destination municipalities. We use data from the 1991 Census on individuals aged between 18-65 in municipalities covered by the *PNAD* survey. Low education individuals are those with incomplete elementary schooling. Earnings are measured in R$ of 2010.

Table 4: **Migration outflows induced by weather shocks**

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall$_{t-1}$	-0.099***	-0.086***	-0.087***	-0.086***	-0.088***	-0.094***
	(0.028)	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)
Rainfall$_{t-2}$			0.042	0.053		
			(0.032)	(0.033)		
Rainfall$_{t-3}$				0.056*		
				(0.031)		
Rainfall$_{t}$					-0.041	
					(0.032)	
Rainfall$_{t+1}$						-0.018
						(0.041)
Observations	14,400	14,400	14,400	14,400	14,400	14,400
Municipalities	960	960	960	960	960	960
R-Squared	0.461	0.472	0.472	0.473	0.473	0.472
F Stat	8.372	5.987	3.134	2.291	4.362	3.049
Time dummies	✓	✓	✓	✓	✓	✓
Municipality dummies	✓	✓	✓	✓	✓	✓
Temperature shocks	✓	✓	✓	✓	✓	✓
Covariates trends		✓	✓	✓	✓	✓

Notes: Each observation is a municipality-year cell. Dependent variable is the number of individuals who left the origin municipality divided by the total population in the 1991 Census. Rainfall is measured as log-deviation from historical average. All specifications include controls for temperature shocks, municipality and year fixed effects. Columns (2)-(6) also control for the log of population in the previous census and include interactions between time dummies and 1991 municipality-level characteristics (age and the share of high school and college educated individuals). Standard errors are clustered at the grid level. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 5: **Effects of migration on earnings**

	(1)	(2)	(3)	(4)
	A. Change in log earnings			
Predicted inflow	-1.655***	-1.323***	-1.182***	-1.265***
	(0.576)	(0.438)	(0.436)	(0.411)
Observations	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684
	B. Change in log earnings, formal sector			
Predicted inflow	-0.848	-0.300	-0.188	-0.462
	(0.674)	(0.488)	(0.489)	(0.444)
Observations	8,162	8,162	8,162	8,162
Municipalities	684	684	684	684
	C. Change in log earnings, informal sector			
Predicted inflow	-1.929***	-1.517***	-1.379***	-1.490***
	(0.607)	(0.439)	(0.441)	(0.390)
Observations	8,156	8,156	8,156	8,156
Municipalities	684	684	684	684
	D. Change in log earnings, self-employed			
Predicted inflow	-1.557***	-1.516***	-1.346***	-1.343***
	(0.450)	(0.391)	(0.383)	(0.405)
Observations	8,133	8,133	8,133	8,133
Municipalities	683	683	683	683
Demographics		✓	✓	✓
Time dummies			✓	✓
Covariates trends				✓

Notes: This table shows regression coefficients of change in log earnings against the predicted number of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. Each observation is a municipality-year cell. Column (2) controls for the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Column (3) also include time dummies. In column (4) we add a linear trend of 1991 municipality-level characteristics (age and the shares of high school and college educated individuals). Regressions are weighted by the 1991 native population. Standard errors clustered at the municipality level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 6: **Effects of migration on employment**

	(1)	(2)	(3)	(4)
	A. Change in employment rate			
Predicted inflow	-0.014	-0.033	-0.030	-0.017
	(0.091)	(0.084)	(0.084)	(0.087)
Observations	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684
	B. Change in formal employment rate			
Predicted inflow	-0.316***	-0.323***	-0.305***	-0.289***
	(0.104)	(0.088)	(0.087)	(0.096)
Observations	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684
	C. Change in informal employment rate			
Predicted inflow	0.160**	0.181**	0.166**	0.153**
	(0.079)	(0.075)	(0.075)	(0.076)
Observations	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684
	D. Change in self-employment rate			
Predicted inflow	0.143**	0.109*	0.108*	0.119
	(0.064)	(0.066)	(0.065)	(0.077)
Observations	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684
Demographics		✓	✓	✓
Time dummies			✓	✓
Covariates trends				✓

Notes: This table shows regression coefficients of change in employment rate against the predicted number of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. Each observation is a municipality-year cell. Column (2) controls for the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Column (3) also include time dummies. In column (4) we add a linear trend of 1991 municipality-level characteristics (age and the shares of high school and college educated individuals). Regressions are weighted by the 1991 native population. Standard errors clustered at the municipality level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 7: **Effects of migration on nonwage benefits**

	(1)	(2)	(3)	(4)
	A. Food			
Predicted inflow	-0.342	-0.472	-0.509*	-0.701**
	(0.313)	(0.299)	(0.300)	(0.301)
Observations	8,147	8,147	8,147	8,147
Municipalities	684	684	684	684
	B. Transport			
Predicted inflow	-0.540*	-0.655***	-0.698***	-0.542*
	(0.306)	(0.228)	(0.226)	(0.278)
Observations	8,147	8,147	8,147	8,147
Municipalities	684	684	684	684
	C. Health			
Predicted inflow	-0.443**	-0.546**	-0.562**	-0.226
	(0.212)	(0.239)	(0.248)	(0.218)
Observations	8,147	8,147	8,147	8,147
Municipalities	684	684	684	684
Demographics		✓	✓	✓
Time dummies			✓	✓
Covariates trends				✓

Notes: This table shows regression coefficients of change in the proportions of formal sector workers who receive health insurance, food or transport subsidies against the predicted number of migrants from the Semiarid region in each destination municipality (measured as a fraction of the native working-age population in 1991). Column (2) controls for the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Column (3) also include time dummies. In column (4) we add a linear trend of 1991 municipality-level characteristics (age and the shares of high school and college educated individuals). Regressions are weighted by the 1991 native population. Standard errors clustered at the municipality level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 8: **Effects of migration on unemployment and participation**

	(1)	(2)	(3)	(4)
	A. Change in unemployment rate			
Predicted inflow	0.177**	0.161**	0.153**	0.156**
	(0.084)	(0.063)	(0.065)	(0.064)
Observations	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684
	B. Change in inactivity rate			
Predicted inflow	-0.163**	-0.128**	-0.123*	-0.139**
	(0.079)	(0.064)	(0.064)	(0.067)
Observations	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684
Demographics		✓	✓	✓
Time dummies			✓	✓
Covariates trends				✓

Notes: This table shows regression coefficients of change in unemployment and inactivity rates against the predicted number of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. Each observation is a municipality-year cell. Column (2) controls for the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Column (3) also include time dummies. In column (4) we add a linear trend of 1991 municipality-level characteristics (age and the shares of high school and college educated individuals). Regressions are weighted by the 1991 native population. Standard errors clustered at the municipality level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 9: **Effects of migration on labor market outcomes, by status in the household**

	(1) Employment	(2) Formal	(3) Informal	(4) Self-Employment	(5) Unemployment	(6) Inactivity
			A. Head			
Predicted inflow	-0.067	-0.220***	0.088**	0.065	0.009	0.021
	(0.054)	(0.067)	(0.043)	(0.041)	(0.032)	(0.035)
Observations	8,190	8,190	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684	684	684
			B. Non-head			
Predicted inflow	0.036	-0.085*	0.079**	0.043	0.144***	-0.144**
	(0.064)	(0.050)	(0.040)	(0.033)	(0.043)	(0.059)
Observations	8,190	8,190	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684	684	684
Demographics	✓	✓	✓	✓	✓	✓
Time dummies	✓	✓	✓	✓	✓	✓

Notes: This table shows regression coefficients of change in employment (by sector), unemployment and inactivity rates against the predicted number of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. Each observation is a municipality-year cell. In Panel A we use only individuals identified as the head of the household while in Panel B only those identified as non-head are used. All regressions control for the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; a cubic polynomial of age, include time dummies and are weighted by the 1991 native population. Standard errors clustered at the municipality level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 10: **Impacts of internal migration on labor markets: IV estimates**

	Overall		Formal		Informal		Self-employment	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Change in employment rates							
Migrant inflow	-0.114	-0.033	-0.218***	-0.330***	0.087	0.180**	0.017	0.117*
	(0.078)	(0.095)	(0.075)	(0.093)	(0.063)	(0.086)	(0.056)	(0.071)
First-stage coefficient		.92		.92		.92		.92
First-stage F-statistic		220.6		220.6		220.6		220.6
Observations	8,190	8,190	8,190	8,190	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684	684	684	684	684
	B. Change in log earnings							
Migrant inflow	-0.695**	-1.281***	-0.265	-0.203	-1.147***	-1.494***	-0.693	-1.459***
	(0.295)	(0.465)	(0.309)	(0.527)	(0.392)	(0.485)	(0.465)	(0.441)
First-stage coefficient		.92		.92		.92		.92
First-stage F-statistic		220.6		220.2		220.8		220.4
Observations	8,190	8,190	8,162	8,162	8,156	8,156	8,133	8,133
Municipalities	684	684	684	684	684	684	683	683
Time dummies	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents OLS and IV regression coefficients of labor market outcomes against the number of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. Columns (1), (3), (5) and (7) show OLS estimates and columns (2),(4),(6) and (8) present the IV coefficients. In Panels A and B the dependent variables are the changes by sector in employment rates and log earnings, respectively. All specifications are weighted by the total native population in 1991, include time dummies and control for the log of total native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Bootstrapped standard errors in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 11: **Effects of migration on unemployment and participation: IV estimates**

	Unemployment		Inactivity	
	OLS	IV/2SLS	OLS	IV/2SLS
	(1)	(2)	(3)	(4)
Migrant inflow	0.173**	0.166**	-0.059	-0.133*
	(0.072)	(0.072)	(0.067)	(0.075)
First-stage coefficient		.92		.92
First-stage F-statistic		220.6		220.6
Observations	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684
Time dummies	✓	✓	✓	✓
Demographics	✓	✓	✓	✓

Notes: This table presents OLS and IV regression coefficients of change in unemployment and inactivity rates against the number of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. Columns (1) and (3) show OLS estimates and columns (2) and (4) present the IV coefficients. All specifications are weighted by the total native population in 1991, include time dummies and control for the log of total native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Bootstrapped standard errors in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 12: **Correlation between predicted migration from the Semiarid and other regions**

	(1)	(2)	(3)
	Migrants from other regions		
Predicted inflow	0.217	0.006	0.198
	(2.854)	(2.823)	(2.846)
Observations	8,190	8,190	8,190
Municipalities	684	684	684
Time dummies	✓	✓	✓
Municipality dummies	✓	✓	✓
Demographics		✓	✓
Covariates Trends			✓

Notes: This table shows regression coefficients of the inflow of migrants coming from other regions against the predicted number of migrants from the Semiarid region in each destination municipality, both measured as a fraction of the native working-age population in 1991. All specifications are weighted by total native population in 1991 and include municipality and year fixed effects. Column (2) controls for the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. In column (3) we add a linear trend of 1991 municipality-level characteristics (age and the shares of high school and college educated individuals). Standard errors clustered at the municipality level in parenthesis.*** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 13: **Migration and changes in log earnings, by industry**

	(1)	(2)	(3)	(4)
	A. Agriculture			
Predicted inflow	-2.476	-0.709	-0.693	-0.391
	(2.222)	(1.863)	(1.821)	(1.866)
Observations	6,251	6,251	6,251	6,251
Municipalities	661	661	661	661
	B. Manufacturing			
Predicted inflow	-1.003*	-0.866	-0.667	-0.467
	(0.584)	(0.578)	(0.578)	(0.579)
Observations	7,902	7,902	7,902	7,902
Municipalities	683	683	683	683
	C. Services			
Predicted inflow	-1.319**	-0.971**	-0.830**	-1.042***
	(0.570)	(0.386)	(0.386)	(0.357)
Observations	8,175	8,175	8,175	8,175
Municipalities	684	684	684	684
Demographics		✓	✓	✓
Time dummies			✓	✓
Covariates trends				✓

Notes: This table shows regression coefficients of change in log earnings by industry against the predicted number of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. Each observation is a municipality-year cell. Column (2) controls for the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Column (3) also include time dummies. In column (4) we add a linear trend of 1991 municipality-level characteristics (age and the shares of high school and college educated individuals). Regressions are weighted by the 1991 native population. Standard errors clustered at the municipality level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Appendix A Migrant flows from the Semiarid region

In this section we discuss in more detail our measure of migration between cities and how we structure a yearly panel dataset from the 2000 and 2010 Censi.

A.1 Migration from the Semiarid region

In every round of the Census, there are two questions which allow us to track the migrants and establish their municipalities of origin and destination, as well as the year when they moved.

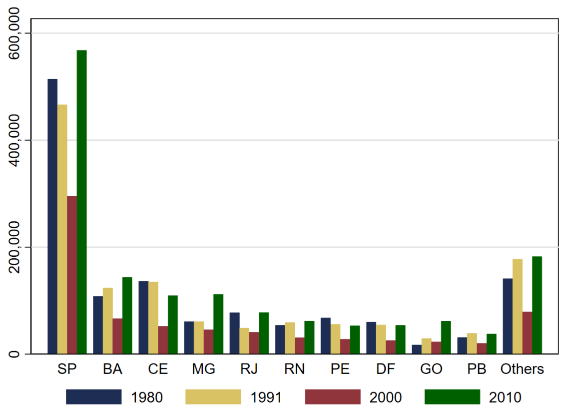
First, in the 2010 Census respondents were asked for how many years they had lived in the current municipality (from one up to ten). With this variable we are able to calculate the year when the individual have migrated. We consider migrant an individual who moved to the current municipality in the previous ten years. In the 2000 Census, interviewees were asked the municipality where they were living five years ago, instead of the last place where they lived, so that we can only identify migrants who came as far as 1996. This is not a major concern in our analysis as 1996 is the first year for which *PNAD* data - the source from which we draw labor market outcomes information - is available.

Second, they were asked what was the municipality where they lived before. Thus, if an individual have migrated from an origin municipality in the Semiarid region, she will be counted as an Semiarid migrant. A limitation is that we can only track one origin location for each person, probably the last municipality where she lived.

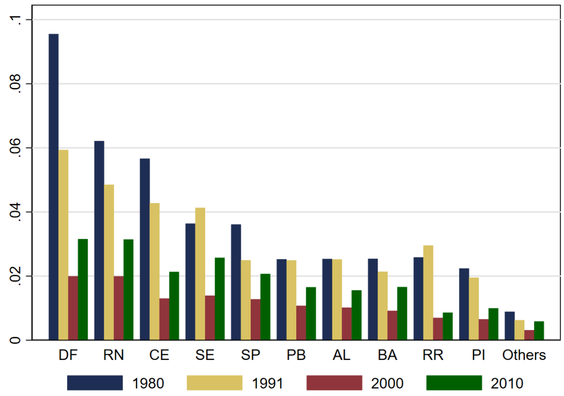
The Semiarid region has always been an important source of migrants for the rest of the country. Figure A1 shows that these migrants tend to be historically concentrated in some states. São Paulo alone harbored over 30 percent of the people arriving from the Semiarid in the last four decades. However, in relative terms incoming migrants represented a population increase of above 2% for the top 10 receiving states.

Table 3 compares migrants to low and high education natives. Migrants are slightly more educated and earn slightly less than low educated natives. They also have similar likelihood of working part time and being in the formal sector when compared to low education natives. On the other hand, high education natives are more likely to work in the formal sector, and have considerably higher pay. Table A1 shows that top occupations for migrants (e.g. typically bricklayer for men, domestic worker for women) are also top occupations for low education natives, but not for the skilled. Also, the same five industries that concentrate over 80% of working migrants also employ a similar share of low education workers (see Table A2).

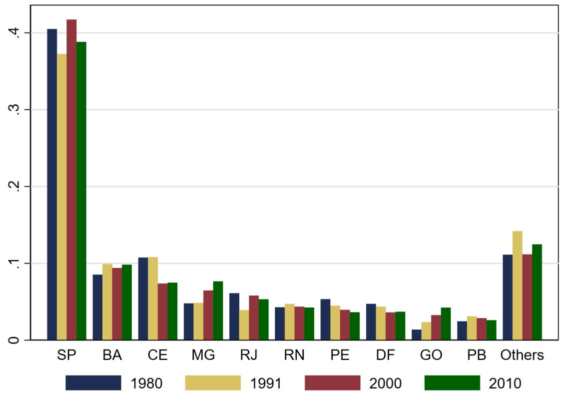
Figure A1: Top destinations for migrants from the Semiarid region



(a) Absolute number of Semiarid's migrants



(b) Semiarid's migrants as a fraction of total population



(c) Semiarid's migrants as share of total migration

Notes: This figure presents the main destination states chosen by migrants from the Semiarid region. Panel (a) shows the absolute number of migrants leaving the Semiarid region to non-Semiarid state. Panel (b) presents the same inflow measured as a fraction of total population in the state while in Panel (c) that number is measured as a share of the total number of migrants in each state. In each panel, states are ranked by the respective average across years. *Data source*: Census microdata (IBGE).

Table A1: **Main occupations for employed people: Migrants vs Natives**

	Position	Occupation	Share of employment	Cumulative
Migrants	1	Domestic worker	13.8	13.8
	2	Bricklayer	9.6	23.4
	3	Non-specified occupations	9.1	32.5
	4	Salesperson	9.1	41.5
	5	Rural worker	3.6	45.2
	6	Janitor	3.0	48.2
	7	Office assistant	2.6	50.8
	8	Tailor	2.5	53.3
	9	Driver	2.3	55.5
	10	Security guard	2.0	57.5
Low-ed. natives	1	Rural worker	10.8	10.8
	2	Bricklayer	8.2	19.0
	3	Salesperson	8.1	27.0
	4	Domestic worker	7.8	34.8
	5	Non-specified occupations	6.0	40.8
	6	Driver	5.7	46.5
	7	Janitor	3.6	50.1
	8	Tailor	2.9	53.0
	9	Cook	1.7	54.7
	10	Mechanic	1.7	56.5
High-ed. natives	1	Salesperson	8.9	8.9
	2	Office assistant	7.9	16.7
	3	Non-specified occupations	4.4	21.1
	4	Tradesperson	3.1	24.2
	5	Secretary	3.1	27.2
	6	Driver	2.6	29.9
	7	Office supervisor	2.6	32.5
	8	Military	2.0	34.5
	9	Teacher	2.0	36.4
	10	Nurse	1.8	38.2

Notes: This table presents the top ten occupations for workers in the destination municipalities, using data from the 1991 Census.

Table A2: **Main industries for employed people: Migrants vs Natives**

	Position	Industry	Share of employed	Cumulative
Migrants	1	Hospitality	31.0	31.0
	2	Manufacturing	19.8	50.8
	3	Retail	14.3	65.1
	4	Construction	13.0	78.2
	5	Agriculture/Mining	5.6	83.7
	6	Health/Education	5.4	89.1
	7	Transport/Communication	4.0	93.1
	8	Other Services	2.5	95.5
	9	Public Sector	2.5	98.0
	10	Professional Services	2.0	100.0
Low-ed. natives	1	Hospitality	25.5	25.5
	2	Manufacturing	18.8	44.3
	3	Agriculture/Mining	14.8	59.2
	4	Retail	12.6	71.8
	5	Construction	10.9	82.7
	6	Transport/Communication	6.0	88.7
	7	Health/Education	4.9	93.6
	8	Public Sector	3.1	96.7
	9	Professional Services	1.9	98.5
	10	Other Services	1.5	100.0
High-ed. natives	1	Health/Education	18.8	18.8
	2	Manufacturing	17.5	36.3
	3	Retail	16.8	53.1
	4	Hospitality	12.0	65.1
	5	Public Sector	9.2	74.3
	6	Professional Services	7.4	81.7
	7	Other Services	6.8	88.5
	8	Transport/Communication	4.9	93.3
	9	Agriculture/Mining	3.5	96.9
	10	Construction	3.1	100.0

Notes: This table presents the top ten industries for workers in the destination municipalities, using data from the 1991 Census.

Appendix B Shift-share instrument

In this section we discuss the weather data and provide further details about how we construct our instrument. We also show that our results are robust to an alternative measure of weather shocks.

B.1 Weather data

Our main source for weather data comes from the CRUTS v4, a gridded dataset produced by the Climatic Research Unit at the University of East Anglia (Harris et al., 2020). It provides information on monthly precipitation and temperature covering the whole globe (except Antartica) from 1901 to 2018. The grid resolutions is $0.25° \times 0.25°$ (around 56km^2) and is created by interpolation from ground-based weather stations around the world.

We use the R package 'geobr' (Carabetta et al., 2020) to download the shapefile of Brazilian municipalities and georreference the coordinates from each municipality's centroid and keep only municipalities that belong to the Semiarid region. Then, for each municipality, we find the grid's four points which are closest to it's centroid and calculate the average level of precipitation and temperature from this points, weighted by the inverse distance to the centroid.

This procedure results in a dataset of monthly averages of precipitation and temperature for each municipality in the Semiarid, from 1901 to 2018, which we aggregate in yearly measures. Precipitation is defined as the sum of monthly levels and temperature as the average. For each municipality we calculate the historical mean from both variables and take log of the levels and long term averages.

Finally, our weather shock variables are defined as

$$Rainfall_{ot} = \ln\left(\sum_{\tau \in \{GS\}} r_{o\tau t}\right) - \ln(\bar{r}_o) \tag{B1}$$

where $r_{o\tau t}$ is the rainfall in municipality of origin o in month τ of year t, and $\bar{r}_o$ is the municipality's historical average precipitation for the same months. The index τ covers the 6-month growing season (GS). Temperature is calculated in a similar way, but using the average instead of summation to create yearly data. In our main specifications, we use data from the Semiarid's growing season (from November to April), but results are very similar when we use the full year (see Table B1).

B.2 Alternative measures of weather

One possible concern about our measure of weather is that we focus on rainfall levels, controlling for temperature variation, to predict the flow of migrants leaving the Semiarid region. This may be problematic because we cannot account for the presence of groundwater or any other factors that influence water balance. To circumvent this issue

Table B1: **Migration outflows induced by weather shocks (12 months)**

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall_{t-1}	-0.126***	-0.120***	-0.118***	-0.128***	-0.121***	-0.124***
	(0.033)	(0.035)	(0.036)	(0.036)	(0.035)	(0.035)
Rainfall_{t}			-0.032	-0.055	-0.029	
			(0.041)	(0.042)	(0.040)	
Rainfall_{t-2}			0.053	0.069*		
			(0.040)	(0.041)		
Rainfall_{t-3}				0.006		
				(0.035)		
Rainfall_{t+1}						-0.040
						(0.042)
Observations	14,400	14,400	14,400	14,400	14,400	14,400
Municipalities	960	960	960	960	960	960
R-Squared	0.461	0.469	0.469	0.470	0.469	0.469
F Stat	8.033	7.232	3.626	3.491	4.398	4.687
Time dummies	✓	✓	✓	✓	✓	✓
Municipality dummies	✓	✓	✓	✓	✓	✓
Temperature shocks	✓	✓	✓	✓	✓	✓
Covariates trends		✓	✓	✓	✓	✓

Notes: Each observation is a municipality-year cell. Dependent variable is the number of individuals who left the origin municipality divided by the total population in the 1991 Census. Rainfall is measured as log-deviation from historical average. All specifications include controls for temperature shocks, municipality and year fixed effects. Columns (2)-(6) also control for the log of population in the previous census and include interactions between time dummies and 1991 municipality-level characteristics (age and the share of high school and college educated individuals). Standard errors are clustered at the grid level. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

we gather new data from Xavier et al. (2016), who provides a gridded dataset with daily averages of precipitation and potential evaporation, from 1980 to 2013, based on ground data from weather stations interpolated to create high-resolution grids (0.25° $\times$ 0.25°) across the Brazilian territory. They calculate potential evaporation using maximum and minimum temperatures, solar radiation, relative humidity and wind speed. We aggregate the daily precipitation and evaporation data into monthly measures and follow Cavalcanti (2018) to construct a measure of drought severity, the aridity index, as follows:

$$AI_{mt} = \frac{\sum_{\tau \in \{GS\}} PE_{m\tau t}}{\sum_{\tau \in \{GS\}} Pr_{m\tau t}} \tag{B2}$$

where $PE_{m\tau t}$ is the potential evaporation in the municipality m, at the month τ of the growing season(GS) in year t. Then we standardize this measure to simplify interpretation and calculate de aridity index z-score as

$$Z_{mt}^{AI} = \frac{\left(AI_{mt} - \overline{AI}\right)}{AI_{sd}} \tag{B3}$$

We show in Table B2 that this alternative measure is also strongly correlated with the migration outflow rate. Including up to three lags and one lead does not affect the main coefficient, neither does the inclusion of controls. In Panel B we regress outflow rate on a categorical variable indicating the quartile of the Aridity Index z-score. Our estimates show that extreme events of drought increase migration even further.

Table B2: **Migration outflows induced by weather shocks: Aridity Index**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: *Continuous Z-score*						
Aridity Index$_t$	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
Aridity Index$_{t-1}$		0.003***	0.003***	0.003***			
		(0.001)	(0.001)	(0.001)			
Aridity Index$_{t-2}$			0.001	0.001			
			(0.001)	(0.001)			
Aridity Index$_{t-3}$				0.000			
				(0.001)			
Aridity Index$_{t+1}$					0.001		
					(0.001)		
Constant	1.020***	0.995***	0.987***	0.985***	1.015***	-2.022**	
	(0.007)	(0.012)	(0.015)	(0.018)	(0.011)	(0.851)	
	Panel B: *Drought severity*						
Second quartile							0.028**
							(0.014)
Third quartile							0.010
							(0.016)
Fourth quartile							0.076***
							(0.019)
Constant							1.024***
							(0.011)
Observations	14,400	14,400	14,400	14,400	14,400	14,400	14,400
Municipalities	960	960	960	960	960	960	960
R-Squared	0.461	0.462	0.462	0.462	0.461	0.470	0.462
Time dummies	✓	✓	✓	✓	✓	✓	✓
Municipality dummies	✓	✓	✓	✓	✓	✓	✓
Demographics						✓	

Notes: Each observation is a municipality-year cell. Dependent variable is the number of individuals who left the origin municipality divided by the total population in the 1991 Census. Aridity Index is measured as the municipality z-score of the ratio between evaporation and precipitation accumulated from November to April. All specifications include municipality and year fixed effects. Column (6) also control for the log of population in the previous census and include interactions between time dummies and 1991 municipality-level characteristics (age and the share of high school and college educated individuals). Drought severity measures are the quartiles of the Aridity Index z-score. Standard errors are clustered at the municipality level. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Appendix C Inference

In this appendix we address the issue raised by Adao et al. (2019) who argued that in the typical shift-share design standard errors may be underestimated because the regression residuals are correlated across units with similar shares.

We present a convenient alternative based on our equivalence result: estimating SSIV coefficients at the level of identifying variation (shocks) can yield asymptotically valid standard errors. The validity of this solution requires an additional assumption on the structure of the included controls (producing standard errors that are conservative otherwise).

We follow Borusyak et al. (2021) to provide valid standard errors for our setting. They show that the shift-share parameter β can be equivalently estimated at the level of identifying variation. In our setup, this correspond to taking destination-level outcomes and endogenous variables, calculate its share-weighted averages for each origin municipality and use the shocks as instruments to estimate the parameter β. They argue that even if the shares are not exogenous their approach renders a consistent estimator. More importantly for this section, they also demonstrate that this produces asymptotically valid standard errors in the framework of Adao et al. (2019). More specifically, we estimate the following IV regression

$$\bar{y}_{ot} = \alpha + \beta \bar{m}_{ot} + \bar{\varepsilon}_{ot} \tag{C4}$$

where $\bar{v}_{ot} = \frac{\sum_d s_{od} v_{dt}}{\sum_d s_{od}}$ is a share-weighted average of the outcomes y on the instrument m at the destination level and the regression is weighted by the average exposure to the shocks $s_o = \sum_d s_{od}$. Put in a more simplistic way, in the traditional shift-share design we take a shock at the origin level and calculate a share-weighted average to use as instrumental variable at the destination. Here, we calculate share-weighted averages of our outcomes and instrument and estimate all the same specifications at the origin-level and present the results in Tables C3-C6.

Table C3: **Inference a la Borusyak et al. (2021)**
IV/2SLS estimates on employment

	(1)	(2)	(3)	(4)
	A. Change in employment rate			
Migrant inflow	-0.015	-0.035	-0.033	-0.018
	(0.068)	(0.069)	(0.050)	(0.063)
Observations	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955
	B. Change in formal employment rate			
Migrant inflow	-0.347***	-0.350***	-0.330***	-0.310***
	(0.071)	(0.065)	(0.045)	(0.056)
Observations	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955
	C. Change in informal employment rate			
Migrant inflow	0.175***	0.196***	0.180***	0.164***
	(0.048)	(0.049)	(0.035)	(0.044)
Observations	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955
	D. Change in self-employment rate			
Migrant inflow	0.156***	0.119***	0.117***	0.128***
	(0.041)	(0.041)	(0.038)	(0.047)
Observations	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955
Demographics		✓	✓	✓
Time dummies			✓	✓
Covariates trends				✓

Notes: This table shows regression coefficients of change in employment rate against the inflow of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. Each observation is a municipality-year cell. Column (2) controls for the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Column (3) also include time dummies. In column (4) we add a linear trend of 1991 municipality-level characteristics (age and the shares of high school and college educated individuals). Regressions are weighted by the 1991 native population. Robust standard errors calculated by the procedure in Borusyak et al. (2021) in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table C4: **Inference a la Borusyak et al. (2021)**
IV/2SLS estimates on earnings

	(1)	(2)	(3)	(4)
	A. Change in log earnings			
Migrant inflow	-1.815***	-1.433***	-1.281***	-1.359***
	(0.268)	(0.244)	(0.164)	(0.205)
Observations	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955
	B. Change in log earnings, formal sector			
Migrant inflow	-0.930***	-0.325*	-0.203	-0.496***
	(0.210)	(0.192)	(0.135)	(0.168)
Observations	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955
	C. Change in log earnings, informal sector			
Migrant inflow	-2.116***	-1.642***	-1.494***	-1.599***
	(0.265)	(0.263)	(0.204)	(0.255)
Observations	8,156	8,156	8,156	8,156
Municipalities	684	684	684	684
	D. Change in log earnings, self-employed			
Migrant inflow	-1.708***	-1.642***	-1.458***	-1.441***
	(0.458)	(0.463)	(0.354)	(0.443)
Observations	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955
Demographics		✓	✓	✓
Time dummies			✓	✓
Covariates trends				✓

Notes: This table shows regression coefficients of change in log earnings against the inflow of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. Each observation is a municipality-year cell. Column (2) controls for the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Column (3) also include time dummies. In column (4) we add a linear trend of 1991 municipality-level characteristics (age and the shares of high school and college educated individuals). Regressions are weighted by the 1991 native population. Robust standard errors calculated by the procedure in Borusyak et al. (2021) in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table C5: **Inference a la Borusyak et al. (2021)**
IV/2SLS estimates on unemployment and participation

	(1)	(2)	(3)	(4)
	A. Change in unemployment rate			
Migrant inflow	0.194***	0.174***	0.166***	0.168***
	(0.060)	(0.061)	(0.044)	(0.055)
Observations	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955
	B. Change in inactivity rate			
Migrant inflow	-0.179***	-0.139**	-0.133***	-0.150**
	(0.058)	(0.058)	(0.050)	(0.062)
Observations	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955
Demographics		✓	✓	✓
Time dummies			✓	✓
Covariates trends				✓

Notes: This table shows regression coefficients of change in unemployment and inactivity rates against the inflow of migrants from the Semi-arid region in each destination municipality, measured as a fraction of the native working-age population in 1991. Each observation is a municipality-year cell. Column (2) controls for the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Column (3) also include time dummies. In column (4) we add a linear trend of 1991 municipality-level characteristics (age and the shares of high school and college educated individuals). Regressions are weighted by the 1991 native population. Robust standard errors calculated by the procedure in Borusyak et al. (2021) in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table C6: **Inference a la Borusyak et al. (2021)**
IV/2SLS estimates on nonwage benefits

	(1)	(2)	(3)	(4)
	A. Food			
Migrant inflow	-0.375**	-0.511***	-0.551***	-0.751***
	(0.155)	(0.158)	(0.116)	(0.145)
Observations	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955
	B. Transport			
Migrant inflow	-0.592***	-0.709***	-0.756***	-0.581***
Observations	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955
	C. Health			
Migrant inflow	-0.486**	-0.591***	-0.608***	-0.242
	(0.194)	(0.200)	(0.136)	(0.169)
Observations	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955
Demographics		✓	✓	✓
Time dummies			✓	✓
Covariates trends				✓

Notes: This table shows regression coefficients of change in the proportions of formal sector workers who receive health insurance, food or transport subsidies against the inflow of migrants from the Semiarid region in each destination municipality (measured as a fraction of the native working-age population in 1991). Column (2) controls for the log of the native population in the previous year and changes in the share of individuals with high school and college education; the shares of female, white and black individuals; and a cubic polynomial of age. Column (3) also include time dummies. In column (4) we add a linear trend of 1991 municipality-level characteristics (age and the shares of high school and college educated individuals). Regressions are weighted by the 1991 native population. Robust standard errors calculated by the procedure in Borusyak et al. (2021) in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Appendix D Spatial autocorrelation in weather shocks

Weather events are likely correlated across space. Figure 11 shows that precipitation levels in the Semiarid are similar among nearby municipalities. Potentially this could invalidate the consistency of our estimator given by *Assumption 2 (Many uncorrelated shocks)* discussed in section 3.2. Here we investigate this issue by re-constructing our instrument according to different degrees of aggregation of regions of origin of a migrant - such as a microregion or mesoregion - instead of a municipality. IBGE (1990) defines microregions as "groups of economically integrated municipalities sharing borders and structure of production". Mesoregions are collections of microregions of which not all municipalities share borders.[29] Brazil has 5,565 municipalities, 361 micro and 87 mesoregions overall. The Semiarid has 960 municipalities, 137 micro and 35 mesoregions.

The intuition behind this exercise is that even if weather shocks are spatially correlated among contiguous municipalities, such correlation should decrease as we consider larger areas. Table D2 display Moran's index of spatial auto-correlation of rainfall shocks for each of the three geographic aggregates in columns 1-3.[30] As expected, neighboring municipalities display correlation above 0,94, but it decreases rapidly as we aggregate up to micro and meso regions, to 0,15 and 0,07, respectively.

Table D2 also shows the association between rainfall shocks and migration outflows. Column 1 is identical to Table 4 for reference. Columns 2 and 3 report almost identical point estimates and precision, indicating that we do not lose any significant information by aggregating origin areas. Next we estimate our main specification from Column (3) in Tables 5-7 using instruments corresponding to micro and mesoregion-level aggregation. Tables D3-D5 show that our results associating migration and earnings, employment and nonwage benefits remain virtually unchanged, indicating that spatial autocorrelation among rainfall shocks in origin municipalities are irrelevant to our results.

[29] Table D1 reports summary statistics of our main variables for all both levels of aggregation.

[30] Moran's I is calculated according to the following formula:

$$I = \frac{1}{\sum_i \sum_j w_{ij}} \times \frac{\sum_i \sum_j w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\frac{1}{N}(y_i - \bar{y})^2} \tag{D1}$$

Essentially, it is a correlation coefficient weighted by an appropriate matrix that models how different units are related across space. We use a row-standardized contiguity matrix with the queen criterion, meaning that two localities i and j sharing either borders or vertices are considered 'neighbors' and the entry w_{ij} has a positive value. Row-standardization ensures that weights are positive and no greater than 1. Non-adjacent pairs receive a zero weight. As discussed by Beenstock et al. (2019), Moran's I can be calculated for each period and averaged out with panel data.

Table D1: **Summary statistics: Micro- and meso-regions in the Semiarid**

Panel A - Micro-regions	Mean	Std. Dev.	Min	Max	Obs
Rainfall shock	-0.01	0.20	-0.70	0.47	2,055
Temperature shock	0.01	0.01	-0.01	0.05	2,055
Out-migration	1,500.70	1,371.95	6.00	9,685.00	2,055
Out-migration rate (p.p.)	1.08	0.41	0.12	3.12	2,055
Population	148,981.55	128,183.19	4,968	752,719	2,055
Area	7,150.16	7,857.60	84.94	55,358.33	2,055
Number of municipalities	8.20	4.56	2.00	26.00	2,055
Panel B: Meso-regions	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**
Rainfall shock	-0.02	0.20	-0.69	0.44	525
Temperature shock	0.01	0.01	-0.01	0.05	525
Out-migration	5,874.18	5,766.16	51.00	34,800.00	525
Out-migration rate (p.p.)	1.08	0.37	0.24	2.32	525
Population	583,156.36	524,776.40	15,499	2,349,152	525
Area	27,986.83	30,649.61	84.94	124,505.71	525
Number of municipalities	37.20	21.51	10.00	118.00	525

Notes: Rainfall is measured in mm. Temperature is measured in degrees Celsius. Migration outflow (inflow) rate are the share of migrants over local (native) population. Area is measured in km^2.

Table D2: **Migration outflows induced by weather shocks according to different aggregation levels**

	(1)	(2)	(3)
	Municipality	Micro-region	Meso-region
Rainfall$_{t-1}$	-0.099***	-0.094***	-0.099***
	(0.028)	(0.032)	(0.025)
Observations	14,400	2,055	525
Origins	960	137	35
R-Squared	0.461	0.764	0.866
Moran's I	0.947	0.158	0.075
Time dummies	✓	✓	✓
Origin dummies	✓	✓	✓
Temperature shocks	✓	✓	✓

Notes: Each observation is a region-year cell. Dependent variable is the number of individuals who left the origin region divided by the total population in the 1991 Census. Rainfall is measured as log-deviation from historical average. All specifications include controls for temperature shocks, municipality and year fixed effects. Moran's I show the spatial correlation in rainfall shocks among origin regions. Standard errors are clustered at the respective region level. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table D3: **Effects of migration on earnings according to different aggregation levels**

	(1)	(2)	(3)
	A. Change in log earnings		
	Municipality	Micro-region	Meso-region
Predicted inflow	-1.182***	-1.037***	-0.916**
	(0.436)	(0.387)	(0.361)
Observations	8,190	8,190	8,190
Destinations	684	684	684
	B. Change in log earnings, formal sector		
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.188	-0.079	0.058
	(0.489)	(0.429)	(0.401)
Observations	8,162	8,162	8,162
Destinations	684	684	684
	C. Change in log earnings, informal sector		
	Municipality	Micro-region	Meso-region
Predicted inflow	-1.379***	-1.192***	-1.053***
	(0.441)	(0.414)	(0.386)
Observations	8,156	8,156	8,156
Destinations	684	684	684
	D. Change in log earnings, self-employed		
	Municipality	Micro-region	Meso-region
Predicted inflow	-1.346***	-1.256***	-1.146***
	(0.383)	(0.362)	(0.347)
Observations	8,133	8,133	8,133
Destinations	684	684	684
Demographics	✓	✓	✓
Time dummies	✓	✓	✓

Notes: This table shows regression coefficients of change in log earnings against the predicted number of migrants from the Semiarid region in each destination municipality (excluding those in the Northeast region), measured as a fraction of the native working-age population in 1991. Column (1) replicates the same results from Column (3) of Table 5. In columns (2) and (3) we aggregate the origin-level shocks at the micro- and meso-region levels, respectively. All specifications use the same set of controls defined in Table 5. Regressions are weighted by the 1991 native population. Standard errors clustered at the municipality level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table D4: **Effects of migration on employment according to different aggregation levels**

	(1)	(2)	(3)
	A. Change in employment rate		
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.030	-0.020	-0.015
	(0.084)	(0.082)	(0.081)
Observations	8,190	8,190	8,190
Destinations	684	684	684
	B. Change in formal employment rate		
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.305***	-0.286***	-0.286***
	(0.087)	(0.080)	(0.077)
Observations	8,190	8,190	8,190
Destinations	684	684	684
	C. Change in informal employment rate		
	Municipality	Micro-region	Meso-region
Predicted inflow	0.166**	0.157**	0.172***
	(0.075)	(0.069)	(0.065)
Observations	8,190	8,190	8,190
Destinations	684	684	684
	D. Change in self-employment rate		
	Municipality	Micro-region	Meso-region
Predicted inflow	0.108*	0.109*	0.099*
	(0.065)	(0.060)	(0.056)
Observations	8,190	8,190	8,190
Destinations	684	684	684
Demographics	✓	✓	✓
Time dummies	✓	✓	✓

Notes: This table shows regression coefficients of change in the proportions of employed natives, by sector, against the predicted number of migrants from the Semiarid region in each destination municipality (excluding those in the Northeast region) measured as a fraction of the native working-age population in 1991. Column (1) replicates the same results from Column (3) of Table 6. In columns (2) and (3) we aggregate the origin-level shocks at the micro- and meso-region levels, respectively. All specifications use the same set of controls defined in Table 6. Regressions are weighted by the 1991 native population. Standard errors clustered at the municipality level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table D5: **Effects of migration on nonwage benefits according to different aggregation levels**

	(1)	(2)	(3)
	A. Food		
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.509*	-0.451*	-0.433*
	(0.300)	(0.269)	(0.253)
Observations	8,147	8,147	8,147
Destinations	684	684	684
	B. Transport		
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.699***	-0.629***	-0.578***
	(0.226)	(0.209)	(0.195)
Observations	8,147	8,147	8,147
Destinations	684	684	684
	C. Health		
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.562**	-0.495**	-0.443**
	(0.248)	(0.232)	(0.214)
Observations	8,147	8,147	8,147
Destinations	684	684	684
Demographics	✓	✓	✓
Time dummies	✓	✓	✓

Notes: This table shows regression coefficients of change in the proportions of formal sector workers who receive health insurance, food or transport subsidies against the predicted number of migrants from the Semiarid region in each destination municipality (excluding those in the Northeast region), measured as a fraction of the native working-age population in 1991. Column (1) replicates the same results from Column (3) of Table 7. In columns (2) and (3) we aggregate the origin-level shocks at the micro- and meso-region levels, respectively. All specifications use the same set of controls defined in Table 7. Regressions are weighted by the 1991 native population. Standard errors clustered at the municipality level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table D6: **Inference a la Borusyak et al. (2021)**
Migration on earnings with alternative clustering

	(1)	(2)	(3)
	A. Change in log earnings		
Predicted inflow	-1.182***	-1.182***	-1.182***
	(0.116)	(0.189)	(0.359)
Observations	11,460	11,460	11,460
Regions	955	137	35
	B. Change in log earnings, formal sector		
Predicted inflow	-0.188	-0.188	-0.188
	(0.124)	(0.198)	(0.344)
Observations	11,460	11,460	11,460
Regions	955	137	35
	C. Change in log earnings, informal sector		
Predicted inflow	-1.378***	-1.378***	-1.378***
	(0.110)	(0.174)	(0.320)
Observations	11,460	11,460	11,460
Regions	955	137	35
	D. Change in log earnings, self-employed		
Predicted inflow	-1.346***	-1.346***	-1.346***
	(0.086)	(0.126)	(0.225)
Observations	11,460	11,460	11,460
Regions	955	137	35
Demographics	✓	✓	✓
Time dummies	✓	✓	✓
Clusters level	Municipality	Micro-region	Meso-region

Notes: This table shows regression coefficients of change in log earnings against the predicted number of migrants from the Semiarid region at the origin municipality level, using the procedure from Borusyak et al. (2021). In Column (1) standard errors are clustered at the municipality level while in Columns (2) and (3) the cluster levels are micro- and meso-region respectively. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table D7: **Inference a la Borusyak et al. (2021)**
Migration on employment with alternative clustering

	(1)	(2)	(3)
	A. Change in employment rate		
Predicted inflow	-0.030	-0.030	-0.030
	(0.023)	(0.038)	(0.064)
Observations	11,460	11,460	11,460
Regions	955	137	35
	B. Change in formal employment rate		
Predicted inflow	-0.305***	-0.305***	-0.305***
	(0.024)	(0.042)	(0.064)
Observations	11,460	11,460	11,460
Regions	955	137	35
	C. Change in informal employment rate		
Predicted inflow	0.166***	0.166***	0.166***
	(0.020)	(0.033)	(0.049)
Observations	11,460	11,460	11,460
Regions	955	137	35
	D. Change in self-employment rate		
Predicted inflow	0.108***	0.108***	0.108**
	(0.017)	(0.027)	(0.044)
Observations	11,460	11,460	11,460
Regions	955	137	35
Demographics	✓	✓	✓
Time dummies	✓	✓	✓
Clusters level	Municipality	Micro-region	Meso-region

Notes: This table shows regression coefficients of change in the proportions of employed natives, by sector, against the predicted number of migrants from the Semiarid region at the origin municipality level, using the procedure from Borusyak et al. (2021). In Column (1) standard errors are clustered at the municipality level while in Columns (2) and (3) the cluster levels are micro- and meso-region respectively. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table D8: **Inference a la Borusyak et al. (2021)**
Migration and nonwage benefits with alternative clustering

	(1)	(2)	(3)
		A. Food	
Predicted inflow	-0.509***	-0.509***	-0.509***
	(0.074)	(0.117)	(0.186)
Observations	11,460	11,460	11,460
Regions	955	137	35
		B. Transport	
Predicted inflow	-0.698***	-0.698***	-0.698***
	(0.038)	(0.057)	(0.092)
Observations	11,460	11,460	11,460
Regions	955	137	35
		C. Health	
Predicted inflow	-0.561***	-0.561***	-0.561***
	(0.056)	(0.095)	(0.139)
Observations	11,460	11,460	11,460
Regions	955	137	35
Demographics	✓	✓	✓
Time dummies	✓	✓	✓
Clusters level	Municipality	Micro-region	Meso-region

Notes: This table shows regression coefficients of change in the proportions of formal sector workers who receive health insurance, food or transport subsidies against the predicted number of migrants from the Semiarid region at the origin municipality level, using the procedure from Borusyak et al. (2021). In Column (1) standard errors are clustered at the municipality level while in Columns (2) and (3) the cluster levels are micro- and meso-region respectively. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.