

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

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Abstract

We investigate the labor market impacts of internal migration in Brazil using a shift-share approach which combines weather-induced migration with past settlement patterns in each destination. Increasing internal migration rate by 1*p.p.* reduces formal employment of natives by 0.13*p.p.*, while increases the share of informal jobs by a similar magnitude. Consistent with downward wage rigidity in the formal sector, we find a smaller negative effect on formal earnings (0.59%) than on informal earnings (0.75%), but also a negative impact on the share of workers receiving nonwage benefits in the range of 0.31*p.p.* to 0.69*p.p.* We complement this evidence using firm-level administrative data on employer-sponsored health insurance contracts. Our results show that firms operating in a municipality that receives more migrants are 1.5*p.p.* less likely to provide health insurance to employees, an effect that is mostly driven by large firms. Finally, less educated individuals bear most of the losses due to migration.

Keywords: Internal migration, wages, employment, nonwage benefits.

JEL Codes: J2, J3, J61, O15.

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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 effects ([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 Semi-arid, 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 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 0.13*p.*, while increases the number of informal² jobs by 0.11*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 or even null.

Regarding compensation in the formal sector, we find a decrease between 0.59% and 1.00% on average earnings and a negative impact on the share of formal workers receiving employer-provided health insurance in the range of 0.31*p.* to 0.47*p.p.*, food vouchers from 0.33*p.p.* to 0.69*p.* and transportation vouchers from 0.37*p.p.* to 0.57*p.p.* Our evidence on employer-sponsored health insurance provision is complemented with firm-level administrative data on health insurance contracts matched to firm-level data on formal sector jobs. We find that firms operating in a municipality that receives more incoming migrants are 1.5*p.p.* less likely to provide health insurance to employees, an effect that is mostly driven by large firms. Despite declines in the provision of non-monetary benefits, which increases labor demand, employment in the formal sector still reduces as mentioned.³ Wages in the formal sector also reduce across the entire wage distribution but more so for higher wage percentiles which is explained by presence of binding minimum wages. For individuals employed in the informal sector or self-employed we show a decrease on earnings between 0.75% and 0.99% mostly concentrated on the bottom third of the wage distribution, consistent with

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

²Our definition of informal sector also include self-employed workers.

³Recent 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.

predictions from a two-sector labor market model where wages can freely adjust in the informal sector, and given a less educated migrant workforce that increases competition relatively more among informal workers.

Heterogeneity analysis shows that these 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 more likely to exit the formal sector and experience a 26% 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.

Next, we find that labor force participation increases by 0.08*p.p.*, almost the same magnitude of the increase in the unemployment rate, which may seem at odds with previous results since earnings fall in the informal sector, 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).⁴

We then turn our attention to the long term impacts of migration on local labor markets in Brazil. Our results indicate that the estimated effects on average earnings in the formal sector remain mostly the same, but in the informal sector decrease even further. In the case of employment, we see a larger negative impact on formal workers while there are no significant effects on informal jobs. As for nonwage benefits the impact on health insurance are mostly the same as in the short run, while the negative effects on transport subsidies are larger and there is no significant effect on food benefits. Also we show that a potential mechanism behind these dynamics is that short-run effects might be partially offset by further internal migration as (mainly low education) natives respond to the adverse effects by moving to markets that were not directly targeted by migrant arrivals.

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).⁵ Some of these studies find that the wages of natives are harmed

⁴The "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.

⁵Rough estimates indicate that global internal migration sits around 740 million (UNDP, 2009), approximately three times the estimated number of international migrants (UN DESA, 2017).

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).⁶ 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).⁷ 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.⁸

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 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 a 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 frame-

⁶Dustmann 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.

⁷See 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.

⁸This 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.

work for interpreting our findings. Section 3 describes the data used in our empirical analysis. In section 4, we explain the empirical strategy and the identifying assumptions we make. In section 5, we present and analyze the main results on employment, wages and nonwage wage benefits. Section 6 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 976,000km².⁹ 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 0.5¹⁰; (iii) risk of drought above 60%¹¹. The average historical precipitation in the Semiarid is about 780mm, as opposed to around 1,500 mm for the rest of the country¹², 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,

⁹That 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.

¹⁰Thornthwaite Index, which combines humidity and aridity for a given area, in the same period.

¹¹Defined as the share of days under hydric deficit, using the period 1970-1990.

¹²See Figure 11.

net migration out of Northeastern states (where most of the Semi-arid is located) was 2.2 and 3.0 million 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 Semi-arid alone searching for better conditions elsewhere in the country. Figure B1 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 Semi-arid 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 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).¹³ 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., 2022). 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.

¹³The minimum wage is above 70% of the median wage in Brazil.

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).

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 benefits provision are considered less rigid than for wages, collective bargaining agreements (CBA) sometimes include clauses pertaining these 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.¹⁴ 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

¹⁴The income tax due cannot be reduced by more than 10%.

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

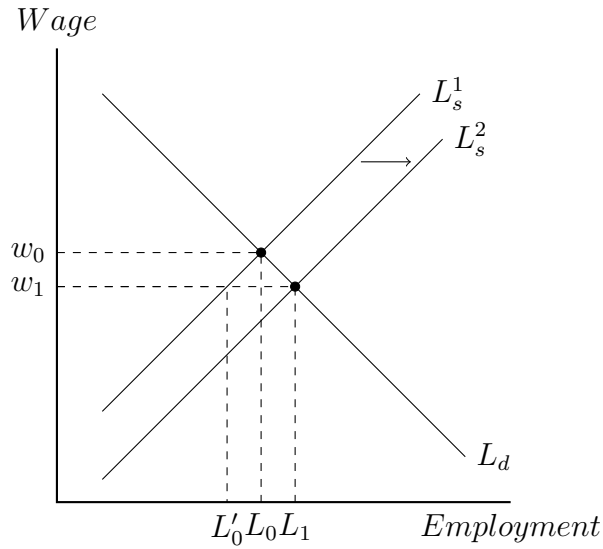
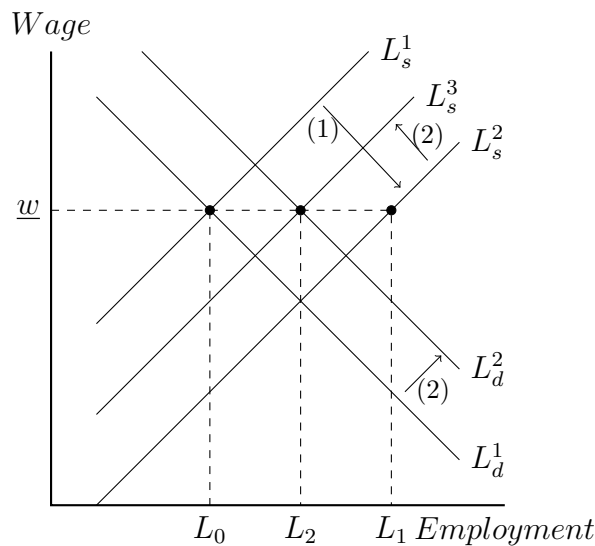


Figure 2: The Effects of Migration with Binding Minimum Wages and Perfect Adjustment of Nonwage Benefits



NOTE: This figure extends the standard competitive labor market case presented in figure 1 to allow for downward wage constraints e.g. minimum wages (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.¹⁵ 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

¹⁵This follows the arguments developed by the labor market model in Card and Lemieux (2001) and Borjas (2003).

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.

So far, we have considered the two sectors – formal and informal – independently, which masks important linkages between them in particular in the production side (see, e.g., [Ulyseas \(2010\)](#) and [Bosch and Esteban-Prete \(2012\)](#)). When the two types of labor are highly substitutes, informal employment and wages can compensate wage rigidities in the formal sector. This should be important to understand the implications of an increase in migration on the labor market particularly where formal wages are rigid thereby increasing the importance of the informal sector as an outside option.

In interpreting our findings, we develop a simple extension of a model with informality in which the formal sector has minimum wage but offer nonwage benefits that are frequently observed in the data (such as health insurance and food subsidy). A motivation for this insight is given in the labor market model developed by [Harris and Todaro \(1970\)](#). In their model minimum wage and labor legislation are the main institutions behind the existence of a formal and an informal sector. We add nonwage benefits in the formal sector as a source of adjustment of total compensation in the presence of minimum wages. We abstract from other sources of labor market frictions, which is explored in much recent work on models of the labor market with monopsony to study immigration effects (e.g. [Amior and Manning \(2020\)](#) and [Amior and Stuhler \(2022\)](#)). They are not needed to understand the mechanisms we emphasize, so we proceed with a simpler approach accounting for unemployment, two employment sectors and intersectoral linkages. Appendix [A](#) presents the model and here we summarize its main predictions.

In such model, the effects of migration may depend on the degree of substitution between formal and informal labor inputs in production and on having the nonwage benefits margin. Considering that migration exogenously shifts the supply of workers to the informal and formal sectors at the destination, our model has clear predictions regarding the direction of effects of migration on employment by sector, unemployment, formal sector nonwage benefits and informal wages.

As [Table A1](#) shows, in the benchmark economy with high production linkages across sectors and nonwage benefits, migration increases unemployment and informal employment but drops nonwage benefits and informal sector wages. Formal employment is unchanged. Under lower intersectoral linkages, the qualitative results the same. However, migration induces a larger fall in informal wages and formal sector benefits. In an economy without nonwage benefits, our main results show that migration has now a negative impact on formal employment as expected, since formal firms cannot adjust benefits after the supply shock from migration. Consequently, unemployment increases relatively more in such economy.

3 Data

We combine information from several sources to consolidate our main dataset. In this section we present some of these sources and variables created. Further details provided in Appendix B.

Migration 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 our study.¹⁶ First, we leverage Census answers about municipality of origin and year of migration to 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.

Weather shocks 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.¹⁸

Labor outcomes 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 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

¹⁶As 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 MCA) in order to avoid potential miscoding regarding migration status or municipality of origin. We use municipality and MCA as synonyms throughout the paper.

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

¹⁸See Appendix C for a detailed description and discussion on this measure.

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 31% having a formal job, the same proportion of informal workers. Unemployment rate is 13% and 24% of individuals are not in the labor force. The average monthly earning is R\$ 637.89, with the formal sector having a substantially higher average (R\$ 788.22) than the informal sector (R\$ 491;28).¹⁹ Among workers employed in the formal sector, 39% receive financial help to cover expenses with food, 36% for transport and 21% 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 B2 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 B3). Overall, this characterization is consistent with greater substitutability between migrants and less skilled natives in the labor market.

4 Empirical Strategy

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

¹⁹Earnings are measured in R\$ (2012).

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

4.1 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

$$\Delta y_{dt} = \alpha + \beta m_{dt} + \gamma \Delta X_{dt} + \psi_t + \epsilon_{dt} \quad (1)$$

where y_{dt} is a vector of labor outcomes at destination municipality d in year t , m_{dt} is the destination migrant inflow from the Semiarid region, X_{dt} are destination-level controls, ψ_t absorb time fixed effects and ϵ_{dt} is the error term. The main challenge to identify β is that the observed migration, m_{dt} , is the equilibrium between demand and supply of migrants. Another issue is that the error term, ϵ_{dt} , may include unobserved characteristics that could be correlated with migration inflows. In particular, migrants could choose a specific destination municipality due to demand shocks leading to higher wages or job prospects. By differencing the outcome variables we can account for time-invariant unobserved characteristics that could be correlated with migrant inflows, but not the time-varying confounders which would potentially bias OLS estimates.

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 rate²¹ from origin municipality o in year t , using weather shocks in the previous year:

$$m_{ot} = \alpha + \beta' Z_{ot-1} + \phi_o + \delta_t + \varepsilon_{ot} \quad (2)$$

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:

$$\widehat{M}_{ot} = \widehat{m}_{ot} \times P_o \quad (3)$$

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, defining our shift-share instrumental variable (SSIV) as

$$\widehat{m}_{dt} = \sum_{o=1}^O \frac{s_{od} \times \widehat{M}_{ot}}{P_d} \quad (4)$$

where s_{od} is the share of migrants from origin municipality o who lived in the destination

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

area d in 1991²² and P_d is total population at d in 1991.²³ Thus our instrument \tilde{m}_{dt} can be 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.²⁴

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

$$\Delta y_{dt} = \alpha + \beta \tilde{m}_{dt} + \gamma \Delta X_{dt} + \psi_t + \epsilon_{dt} \quad (5)$$

We follow [Borusyak et al. \(2021\)](#) and calculate an origin-level weighted average version of equation 5, that uses the exposure shares s_{od} as weights, and results in the transformed reduced form relationship

$$\bar{y}_{ot} = \alpha + \beta \widehat{M}_{ot} + \bar{\epsilon}_{ot} \quad (5')$$

In Appendix D we provide a detailed derivation of the transformation performed and discuss the assumptions needed for identification.

One additional advantage of using the origin-level shocks concerns 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. But, [Borusyak et al. \(2021\)](#) show that by using the shock-level relationship instead of the destination-level one can obtain standard errors that converge to those obtained by the [Adao et al. \(2019\)](#)’s correction procedure.

4.2 Weather-induced migration

We begin the exploration of our first-stage results by estimating variations of specification 2 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

²²We 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.

²³In appendix C we further discuss our shift-share instrument in more detail.

²⁴Note that the denominator P_d is only a normalization that helps interpreting the coefficients of interest. It does not play any role in identification.

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.²⁵

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 does 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 1*p.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, \tilde{m}_{ot} and \tilde{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, accumulated over the period 1996-2010. Panel (b) shows the predicted and observed numbers of incoming Semiarid migrants for destination municipalities.

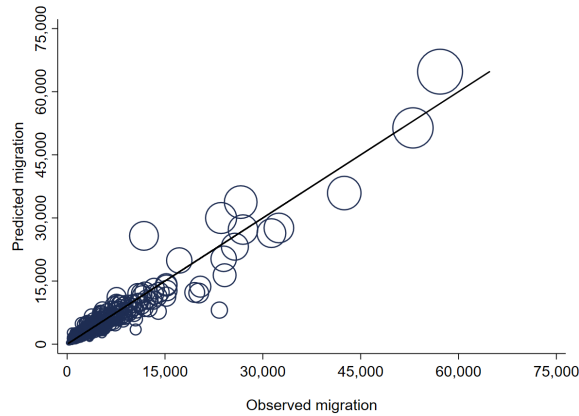
In Appendix C we describe in more detail our data source for weather shocks, discuss alternative measures of weather, and present further details about how we constructed our instrument including predicted and past settlement patterns.

Overall, this analysis shows that our strategy provides a strong first-stage as predicted migration rates, \tilde{m}_{dt} , are strongly correlated with observed migration. Appendix Table D3 reveals that our first-stage point estimates are close to a one-to-one relationship (0.92) - making the magnitude of reduced-form and IV estimates almost identical - and have an F-stat of 2,275.²⁶

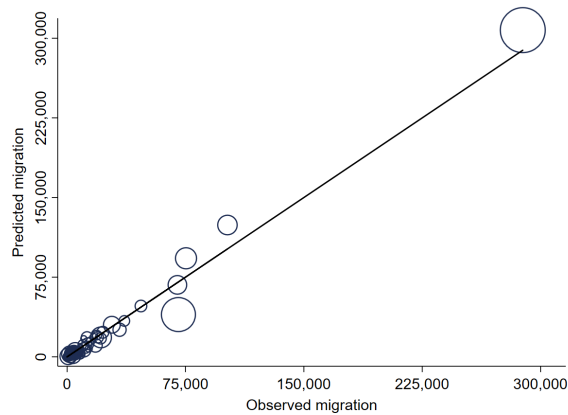
²⁵Similar, but not equal to, as shocks are computed by taking the average of the grid’s four nodes, weighted by the inverse of the distance from each node to the municipality centroid.

²⁶A 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 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).

5 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 native workers' earnings adjust at all in response to the migration flows. Figure 4 summarizes our main findings, while in Table 5 we present several specifications for the SSIV estimates. Column (1) displays a flexible specification, without any control. In column (2) we include time dummies and in column (3) we also control for a vector of destination-level characteristics measured in 1991 (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. All regressions are weighted by the working-age native population in 1991. Standard errors are clustered at the origin municipality level.

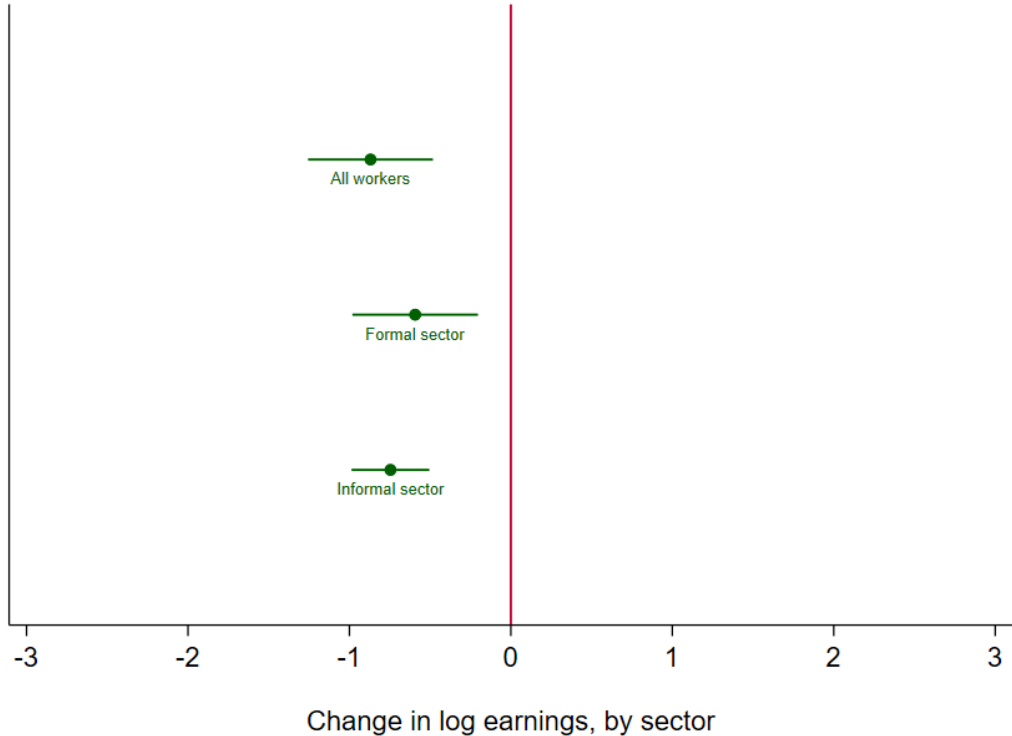
Panel A reveals a strong negative effect of the inflow of Semiarid's migrants on average log earnings for native workers. The inclusion of controls diminishes a little the magnitude of our coefficient of interest, but it does not change substantially our main conclusion. One percentage point increase in the number of migrants reduces earnings by 0.87%. In Panel B we restricted our analysis to native workers holding a formal job, while in Panels C we focus on those in the informal sector, including workers who are self-employed. We find that a one percentage point increase in the inflow of migrants reduces the earnings of formal workers by 0.59% and by 0.53% for those employed in the informal sector.

Any downward wage restrictions such as minimum wages or collective bargaining agreements may alleviate the impacts of the incoming migration on earnings for natives employed in the formal sector. However, in the informal sector, the larger negative impact on earnings is consistent with absence of downward wage rigidity in this sector such that the classic predictions from perfect competition prevail.

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 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.

We find no effect on overall employment, however the inflow of migrants from the Semiarid does affect the composition of workers across sectors. Our estimates in Panels B and C imply that one percentage point increase in the inflow reduces the share of

Figure 4: Effects of internal migration on earnings



Notes: This figure plots origin-level SSIV coefficients on change in log earnings, by sector. Informal sector includes self-employed workers. Controls include time dummies and destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. Green markers are statistically significant at the 5% level.

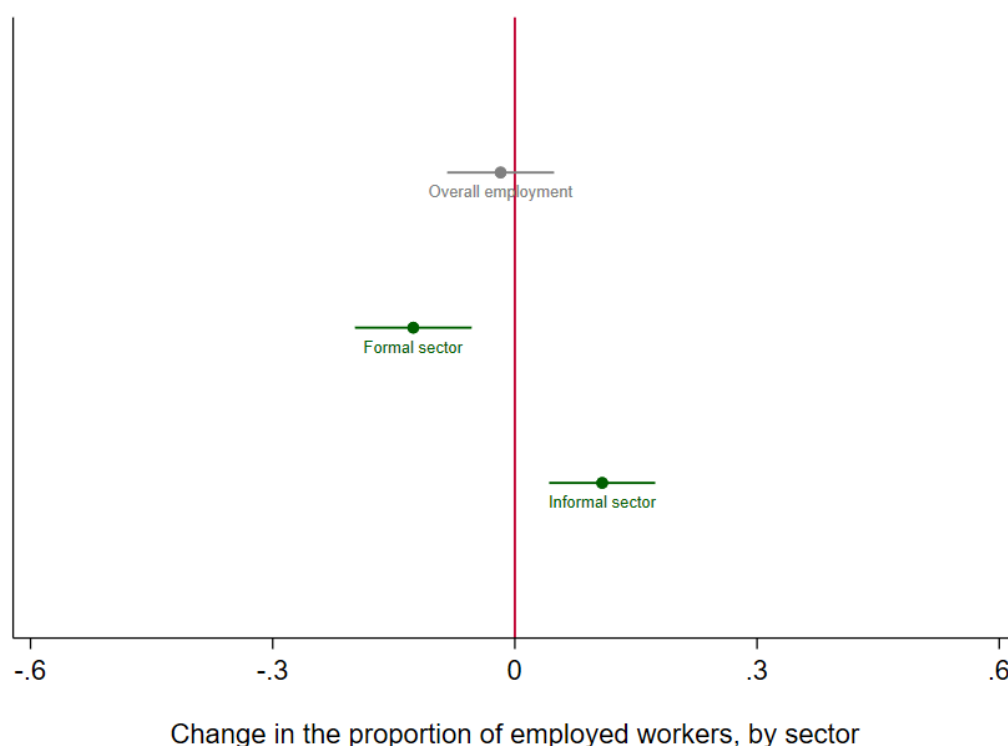
formal employment by 0.13*p.p.*, and increases the share of informal by almost the same amount (0.11*p.p.*).

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 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

Figure 5: Effects of internal migration on employment

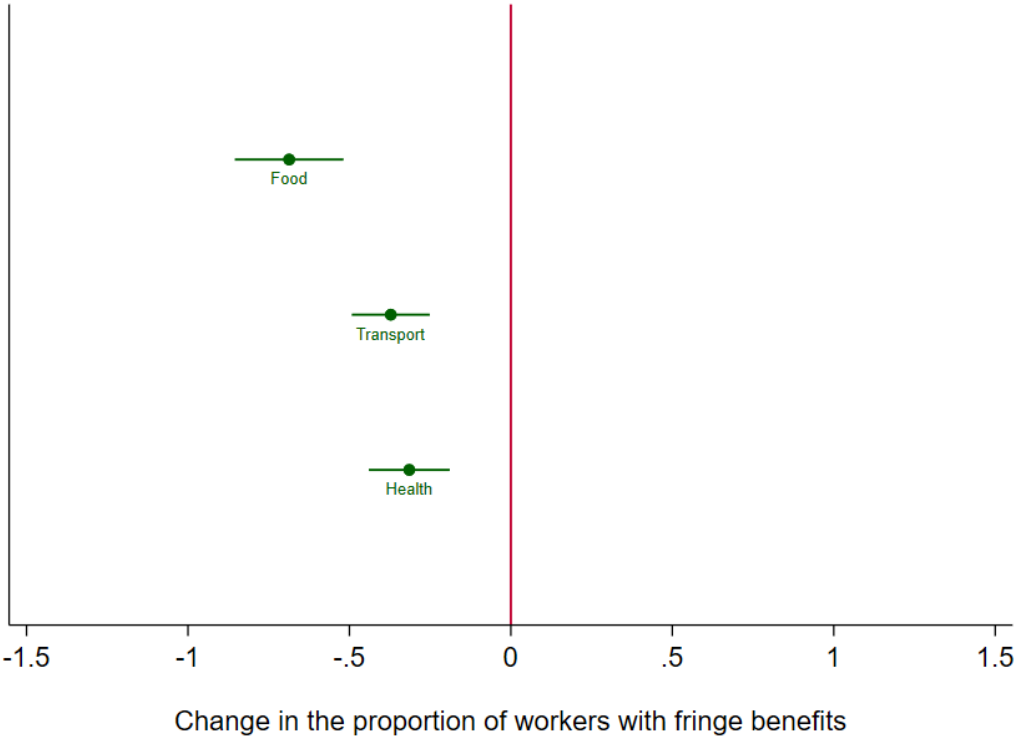


Notes: This figure plots origin-level SSIV coefficients of change in employment rate, by sector, measured as a fraction of the native working-age population in 1991. Informal sector includes self-employed workers. Controls include time dummies and destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. Green markers are statistically significant at the 5% level.

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 food subsidy between 0.33*p.p.* and 0.69*p.p.*, transport between 0.37*p.p.* to 0.52*p.p.*, and health insurance in the range of 0.31*p.p.* to 0.47*p.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, 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.

Figure 6: Effects of internal migration on nonwage compensation



Notes: This figure plots SSIV coefficients on change in the proportions of formal sector workers who receive health insurance, food or transport subsidies. Controls include time dummies and destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. Green markers are statistically significant at the 5% level.

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 (0.09*p.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, as predicted by the model developed in the Appendix A. On the other hand, if the primary earner in the household loses his/her job because of the 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 10, 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 show the SSIV estimates on each decile of earnings, by sector. For those native workers employed in the formal sector, we find smaller impacts at the bottom of the distribution but those effects are stronger for workers at the upper tail. This result is consistent with the rigidity in the formal sector where a minimum wage can limit the negative impacts for low-paid workers.

For informal workers, the impact is substantially stronger for those at the bottom third of the distribution, consistent with classic predictions from perfect competition and greater substitutability between migrants and less skilled natives in this sector. 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.

5.1 Additional evidence: health insurance provision by firms

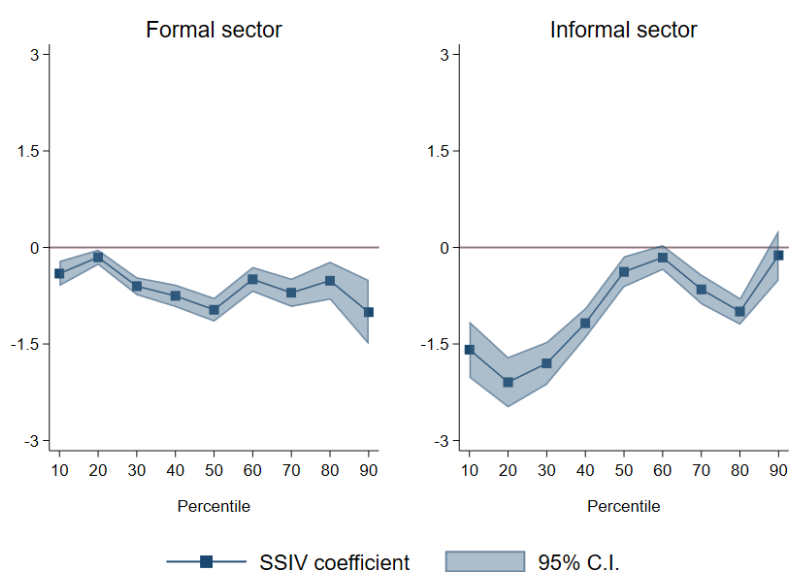
Here we complement our nonwage compensation results by focusing on the behavior of firms as providers of health insurance to their employees.²⁷ Instead of relying on survey data as in our main estimates, we turn to firm-level administrative data on health insurance contracts obtained from *Agência Nacional de Saúde Suplementar (ANS)*, the Brazilian regulatory agency responsible for overseeing the private health industry. They provide information about every employer-sponsored contract signed going back as far as 1940. We have data on the date when the contract was signed and the firm unique identifier, which we can use to merge with *RAIS*, an employer-employee matched dataset obtained from the Ministry of Labor, that provides firm-level data on the near universe of formal employment contracts. We define an indicator variable:

$$y_{idt} = \mathbb{1}(t \geq t^s) \quad (6)$$

for each firm i in the destination municipality d at year t , with t^s being the year when the health insurance is hired. Then we estimate how migration inflow rates at destination

²⁷20% of workers get private health insurance through their employers. In 2018, the average employer-provided health insurance benefit cost on average R\$582, or 17% of total compensation in that same year (ANS, 2018). See section 2.2 for more details.

Figure 7: Effects of predicted migration along the earnings distribution



Notes: This figure plots SSIV coefficients of change in the average of log earnings, in each decile, by sector. Informal sector also includes self-employed workers. Controls include time dummies and destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies.

municipality d affects changes in y_{idt} , that is, the likelihood that firm i provides health insurance to its employees.

In column 1 of Table 9 we find that firms operating in a municipality that receives more incoming migrants are on average less likely to provide health insurance to employees.²⁸ An average migration rate of 0.27pp reported in Table 1 implies a 0.4pp decrease in the share of firms that provide health insurance, or one quarter of the average y_{idt} . In Columns 2-5 we restrict the sample to different bins of firm size. The effect is close to zero and insignificant for firms below 100 employees, but negative and significant for larger firms. This is expected as firms above 100 employees are at least 6 times more likely to provide health insurance as part of compensation.

5.2 Long Run Impacts of Migration

Next we turn our attention to the dynamics of the impact of migration on local labor markets in Brazil. Short and long-run effects might differ as markets adapt to current shocks. Jaeger et al. (2018) report short-run local effects of migration inflows for the US in the 1970s that are more negative than many in the previous literature, suggesting that the initial impact on natives is potentially large. However, they also show that much of this decline is reversed in later periods.

We account for these long run effects by calculating the long differences in the outcome variables from 1996-2001 and 2001-2009.²⁹ We stack the two periods and estimate the same origin-level SSIV regressions from Section 5.

Table 12 shows the long term effects of the inflow of migrants from the Semiárid region on the changes in earnings and employment. In the long-run destination labor markets adjust further, resulting in more negative impacts for the native workers. The average earnings reduce by 0.66% and 1.57% among workers in the formal and informal sectors, respectively. On the employment margin, our estimates show a decrease of .26p.p. in the formal sector, but no significant effect in the informal sector. Such result may be reflecting the dual nature of formal and informal markets. In the more rigid formal sector, the markets adjust more slowly than in the flexible informal sector. Table 13 shows that nonwage benefits also are an important margin of adjustment in the long-run. There is no change in the proportion of workers receiving food vouchers, but the share of natives who receives transport subsidies decreases by 0.75.p and those with health insurance reduce by 0.38p.p..

A potential mechanism behind these dynamics is that short-run effects might be partially offset by further internal migration as natives respond to the adverse effects by moving to markets that were not directly targeted by migrant arrivals. Table 15 reports coefficients of the effect of our predicted shocks on the migration outflows of natives, according to levels of schooling. All estimates are positive but not very precisely

²⁸All the regressions are weighted by the number of employees in the firm in 1996, the first year in our sample.

²⁹PNAD data are not available for the years when the Census are collected - 2000 and 2010.

estimated, and the magnitude is greater for natives of lower education, who are the most affected by the arrivals of Semiarid migrants (see Section 6).

5.3 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 the Semiarid and that from other regions. In Table 14 we show the coefficients from a destination-level regression of the migration inflow rate of migrants from other regions on the predicted inflow rate of migrants from the Semiarid. Column (1) includes time and municipality fixed effects, while in Column (2) we add the same set of controls from our main results. Point estimates are close to zero and not statistically significant in any specification.

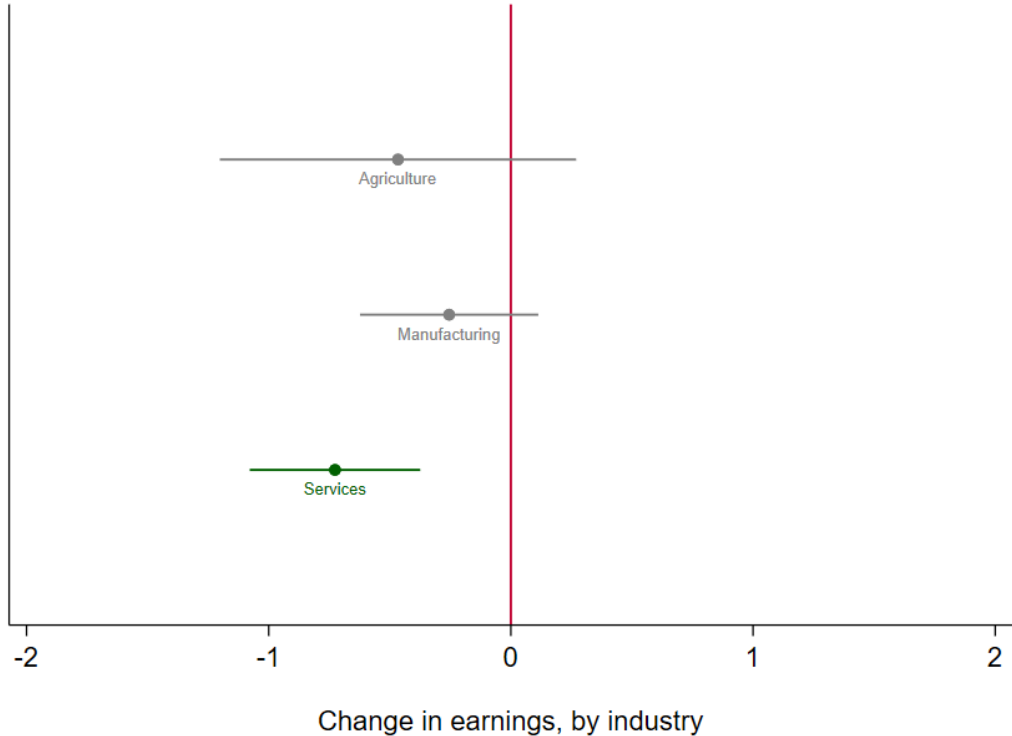
The second issue is that our strategy relies on the assumption that rainfall at origin municipalities affects destination labor markets only through internal migration. One possible violation of this assumption would be if a negative income shock at the origin, due to low rainfall levels, had reduced 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 Figure 8 we report the coefficients from a regression of the predicted inflow rate on changes in log earnings by industry where the individual is employed. There is no statistically significant effects on the earnings for workers in the agricultural or manufacturing industries. All the impact comes from those native workers employed in services, which are less likely to be affected by negative shocks at the origin municipalities.

Finally, we explore the sensitivity of our results according to the degree of aggregation of regions of origin. In Appendix D we argue that 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 E 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.³⁰ First, we document that spatial correlation among shocks decrease dramatically as we consider larger areas. Second, Tables E2-E5 show that our results associating migration and rainfall, earnings, employment and nonwage benefits remain virtually unchanged, indicating that spatial correlation among rainfall shocks in origin municipalities are irrelevant to our results.

³⁰IBGE (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.

Figure 8: Effects of internal migration on earnings



Notes: This figure plots origin-level SSIV coefficients on change in log earnings, by industry. Controls include time dummies and destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. Green markers are statistically significant at the 5% level.

6 Heterogeneous Effects

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 two cases of possible heterogeneity. First, it is possible that migrant shocks cause differential effects according to the size of firms. Second, we test whether the impacts on native workers differ by the education level of the individual.

6.1 Effects by firm size

The effect of an exogenous shock of migrants on native workers may be different for those individuals employed by large firms compared to those in small firms. If we assume that production linkages are lower for larger firms, the model depicted in appendix A predicts that in those firms employment and total compensation should decrease. In Table 11 we confirm this prediction by running the same regressions from Tables 5-7 according to the size of the firm where the individual is employed. We define

large firm those with more than five employees. Our estimates show that, in line with our theory, the negative impacts on employment are more sizable on larger firms, while smaller firms (higher linkages) adjust more on the earnings margin, both in the formal and informal sectors.

6.2 Effects by education level

We also assess whether 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 8 years of schooling, which is equivalent to complete elementary education. In our sample, 58% of natives are low educated.

Figure 9 illustrates the estimates by education level. Panel A shows the effect of predicted migration on the changes in employment rates, by sector and education group. Less educated native individuals are more likely to exit the formal sector and to become informal sector workers compared to those who have higher level of 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 (less educated) 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 10 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

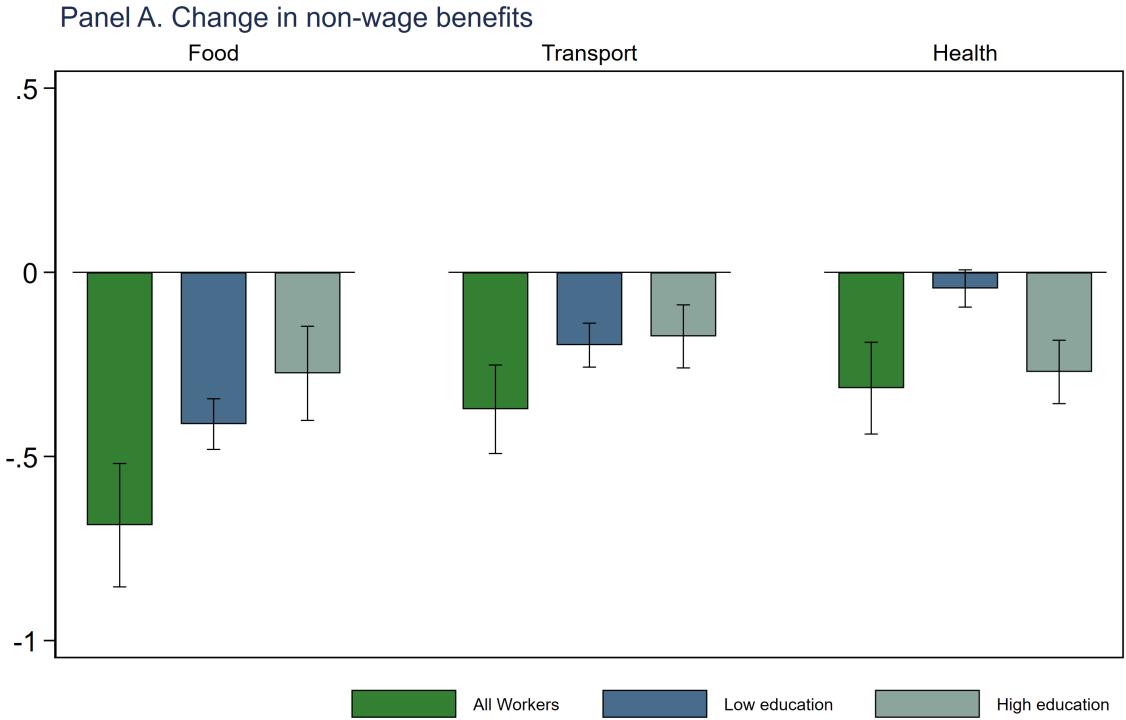
Figure 9: Effects of migration on employment and earnings, by education level



Notes: This figure plots SSIV coefficients of change in labor market outcomes, by education level. 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 SSIV coefficient for a separate regression on the average and by education (low education = up to 8 years of schooling). All regressions are weighted by the working-age native population in 1991, include time dummies and control for destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. The capped lines show the 95% confidence intervals.

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 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.

Figure 10: 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 Semi-arid 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 8 years of schooling). All regressions are weighted by the working-age native population in 1991, include time dummies and control for destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. The capped lines show the 95% confidence intervals.

7 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 for natives in the informal sector which is stronger than that on formal workers. For them, adjustment occurs also through reductions in nonwage benefits such as health insurance, food and transport subsidies. We find that the migration effects on health insurance provision are transmitted at the firm-level. Formal sector firms respond to the increased supply of migrants by delaying or never offering health benefits, consistent with predictions of a two-sector competitive model with minimum wage constraint however with the possibility of adjusting nonwage compensation in the formal sector.

As a result, there is no change in overall employment. This is consistent with workers reallocating to the informal sector 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.

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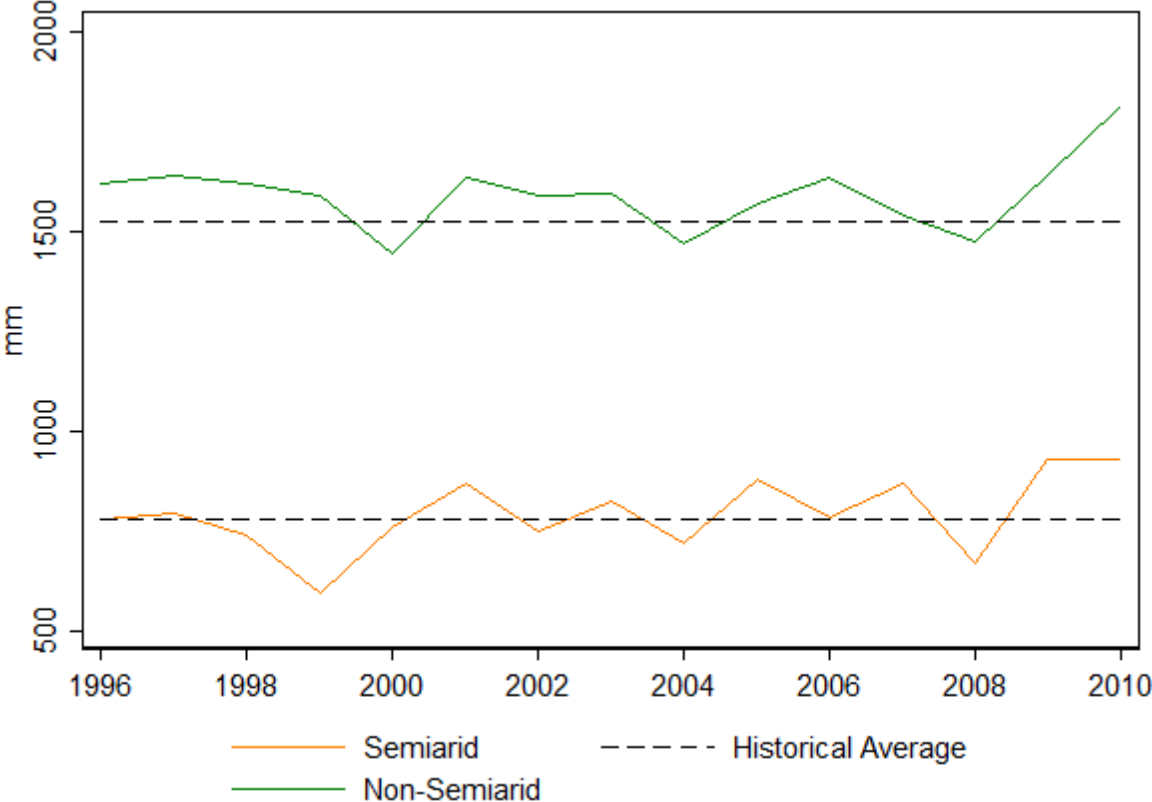
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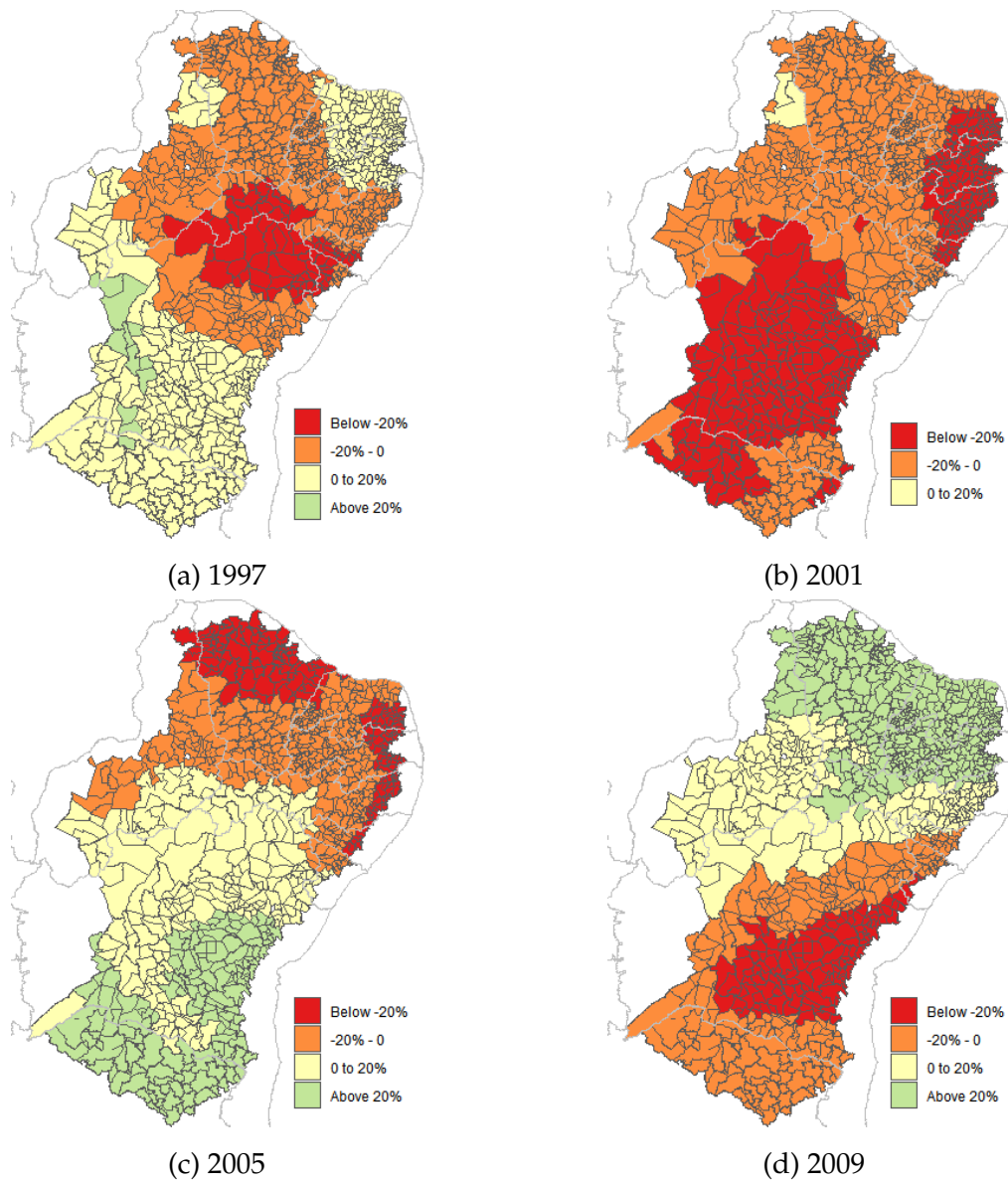
Figures and tables

Figure 11: 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 12: Precipitation levels in the Semiarid region for selected years



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	782.33	248.71	165.49	1,953.17	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	21,377	30,386	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
Rainfall shock	0.04	0.16	-0.77	0.65	8,190
Annual Temperature	23.15	2.82	15.82	28.77	8,190
Temperature shock	0.03	0.02	-0.03	0.08	8,190
In-migration	146.69	896.95	0.00	25,423	8,190
In-migration rate (p.p.)	0.30	1.00	0.00	27.95	8,190
Native population	51,963	231,29	290	4,771,961	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	3.65	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	65.33	15.75	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	31.38	9.05	0	81.80	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	637.89	348.99	60.88	3,582.08	8,190
Formal sector	788.22	439.49	58.67	15,167.10	8,174
Informal sector	491.28	284.28	20	4,941.10	8,172
Nonwage benefits					
	Mean	Std. Dev.	Min	Max	Obs
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. Informal sector also includes self-employed workers. Nonwage benefits are calculated only for native workers employed in the formal sector.

Table 3: Comparative characteristics: Migrants vs Natives

	<i>Migrants</i>		<i>Low-ed. natives</i>		<i>High-ed. natives</i>	
	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*** (0.028)	-0.092*** (0.028)	-0.093*** (0.028)	-0.092*** (0.028)	-0.093*** (0.028)	-0.096*** (0.030)
Rainfall _{t-2}			0.008 (0.030)	0.022 (0.031)		
Rainfall _{t-3}				0.059** (0.028)		
Rainfall _t					-0.047 (0.031)	
Rainfall _{t+1}						-0.059 (0.036)
Observations	14,400	14,400	14,400	14,400	14,400	14,400
Municipalities	960	960	960	960	960	960
R-Squared	0.461	0.465	0.465	0.466	0.465	0.466
F Stat	8.208	3.905	3.545	3.351	3.531	3.620
Time dummies	✓	✓	✓	✓	✓	✓
Municipality dummies	✓	✓	✓	✓	✓	✓
Temperature shocks	✓	✓	✓	✓	✓	✓
Baseline × time		✓	✓	✓	✓	✓

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 the log-deviation from historical average (for the 6 months in the crop growing season). 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)
A. Change in log earnings			
Migrant inflow	-1.323*** (0.143)	-1.252*** (0.142)	-0.869*** (0.197)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
B. Change in log earnings, formal sector			
Migrant inflow	-1.005*** (0.171)	-0.929*** (0.169)	-0.593*** (0.198)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
C. Change in log earnings, informal sector			
Migrant inflow	-0.986*** (0.072)	-0.908*** (0.072)	-0.746*** (0.123)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
Time dummies		✓	✓
Baseline × time			✓

Notes: This table origin-level SSIV coefficients on changes in log earnings, by sector. Each observation is a municipality-year cell. Informal sector also includes self-employed workers. Column (2) include time dummies while Column (3) also controls for destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. All regressions are weighted by the working-age native population in 1991. Standard errors clustered at the origin municipality level in parenthesis. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 6: Effects of migration on employment

	(1)	(2)	(3)
A. Change in employment rate			
Migrant inflow	-0.011 (0.022)	-0.019 (0.022)	-0.018 (0.034)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
B. Change in formal employment rate			
Migrant inflow	-0.312*** (0.025)	-0.317*** (0.025)	-0.126*** (0.037)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
C. Change in informal employment rate			
Migrant inflow	0.301*** (0.029)	0.298*** (0.029)	0.108*** (0.034)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
Time dummies		✓	✓
Baseline × time			✓

Notes: This table origin-level SSIV coefficients on changes in employment rate, by sector. Each observation is a municipality-year cell. Informal sector also includes self-employed workers. Column (2) include time dummies while Column (3) also controls for destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. All regressions are weighted by the working-age native population in 1991. Standard errors clustered at the origin municipality level in parenthesis. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 7: Effects of migration on nonwage benefits

	(1)	(2)	(3)
A. Food			
Migrant inflow	-0.336*** (0.062)	-0.369*** (0.063)	-0.687*** (0.086)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
B. Transport			
Migrant inflow	-0.523*** (0.040)	-0.570*** (0.040)	-0.372*** (0.062)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
C. Health			
Migrant inflow	-0.442*** (0.043)	-0.472*** (0.044)	-0.315*** (0.064)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
Time dummies		✓	✓
Baseline × time			✓

Notes: This table shows origin-level SSIV coefficients on changes in the proportions of formal sector workers who receive health insurance, food or transport subsidies. Each observation is a municipality-year cell. Column (2) include time dummies while Column (3) also controls for destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. All regressions are weighted by the working-age native population in 1991. Standard errors clustered at the origin municipality level in parenthesis. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 8: Effects of migration on unemployment and participation

	(1)	(2)	(3)
A. Change in unemployment rate			
Migrant inflow	0.167*** (0.013)	0.176*** (0.013)	0.094*** (0.020)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
B. Change in inactivity rate			
Migrant inflow	-0.155*** (0.022)	-0.157*** (0.022)	-0.077*** (0.029)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
Time dummies		✓	✓
Baseline × time			✓

Notes: This table shows origin-level SSIV coefficients on changes in unemployment and inactivity rates. Each observation is a municipality-year cell. Column (2) include time dummies while Column (3) also controls for destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. All regressions are weighted by the working-age native population in 1991. Standard errors clustered at the origin municipality level in parenthesis. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 9: Effects of predicted in-migration on employer-provider health insurance

	(1)	(2)	(3)	(4)	(5)
Predicted inflow	-0.015** (0.007)	0.003 (0.002)	-0.004 (0.003)	-0.010** (0.005)	-0.048** (0.022)
Mean of dep. var.	0.0158	0.0131	0.0448	0.0609	0.0758
Observations	4,462,346	4,167,842	138,572	142,100	13,832
Municipalities	682	679	482	608	280
Firms	318,739	297,703	9,898	10,150	988
Time dummies	✓	✓	✓	✓	✓
Firm dummies	✓	✓	✓	✓	✓
Firm size	All firms	1 to 50	51 to 100	101 to 1,000	More than 1,000

Notes: The dependent variable is the difference in the dummy variable that is equal to one for every year greater than or equal to the year when the health insurance contract was signed. The regressor is the predicted number of migrants from the Semiarid region in each destination municipality (excluding those in the Semiarid region), measured as a fraction of the native working-age population in 1991. Our samples comprises a balanced panel of all firms included in RAIS during the period. All the regressions are weighted by the number of employees in the firm in 1996. Standard errors clustered at the municipality level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 10: Effects of migration on labor market outcomes, by status in the household

	(1)	(2)	(3)	(4)	(5)
	Employment	Formal	Informal	Unemployment	Inactivity
A. Head					
Predicted inflow	-0.028*	-0.113***	0.085***	0.018*	0.032**
	(0.015)	(0.021)	(0.019)	(0.011)	(0.013)
Observations	11,460	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955	955
B. Non-head					
Predicted inflow	0.010	-0.013	0.024	0.076***	-0.108***
	(0.024)	(0.019)	(0.018)	(0.014)	(0.019)
Observations	11,460	11,460	11,460	11,460	11,460
Municipalities	955	955	955	955	955
Time dummies	✓	✓	✓	✓	✓
Baseline × time	✓	✓	✓	✓	✓

Notes: This table shows origin-level SSIV coefficients on changes in employment (by sector), unemployment and inactivity rates. Each observation is a municipality-year cell. Informal sector also includes self-employed workers. 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 include time dummies and destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. All regressions are weighted by the working-age native population in 1991. Standard errors clustered at the origin municipality level in parenthesis. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 11: Effects by firm size

	Large firms			Small firms		
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Change in log earnings			A. Change in log earnings		
	Overall	Formal	Informal	Overall	Formal	Informal
Migrant inflow	-0.494*** (0.086)	-0.395*** (0.095)	-0.630*** (0.184)	-0.707*** (0.114)	-0.926*** (0.153)	-1.101*** (0.146)
Observations	11,460	11,460	11,460	11,446	11,446	11,446
Municipalities	955	955	955	955	955	955
	B. Change in employment rate			B. Change in employment rate		
	Overall	Formal	Informal	Overall	Formal	Informal
Migrant inflow	-0.090*** (0.014)	-0.548*** (0.068)	0.458*** (0.070)	0.115*** (0.027)	0.180 (0.110)	-0.065 (0.109)
Observations	11,460	11,460	11,460	11,446	11,446	11,446
Municipalities	955	955	955	955	955	955
	C. Change in non-wage benefits			C. Change in non-wage benefits		
	Food	Transport	Health	Food	Transport	Health
Migrant inflow	-1.115*** (0.102)	-0.639*** (0.065)	-0.391*** (0.085)	0.422*** (0.147)	0.583*** (0.170)	0.246*** (0.075)
Observations	11,460	11,460	11,460	11,446	11,446	11,446
Municipalities	955	955	955	955	955	955
Time dummies	✓	✓	✓	✓	✓	✓
Baseline × time	✓	✓	✓	✓	✓	✓

Notes: This table shows origin-level SSIV coefficients on log earnings, employment rate and the share of native workers receiving non-wage benefits, by firm size. Large firms are those with more than 5 employees. The instrument is the predicted migration, measured as a fraction of the 1991 working-age native population. All specifications include time dummies and destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of women in the total and employed populations; logs of the average household income and size; shares of the population with access to piped water and electricity) interacted with time dummies. All regressions are weighted by the 1991 working-age native population. Standard errors clustered at the origin municipality level in parenthesis. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 12: Long run impacts: earnings and employment

	(1)	(2)	(3)
	Overall	Formal	Informal
A. Change in log earnings			
Migrant inflow	-1.111*** (0.312)	-0.658*** (0.253)	-1.570*** (0.265)
Observations	1910	1910	1910
Municipalities	955	955	955
B. Change in employment rate			
Migrant inflow	-0.305*** (0.051)	-0.257*** (0.048)	-0.048 (0.053)
Observations	1,910	1,910	1,910
Municipalities	955	955	955
Time dummies	✓	✓	✓
Baseline × time	✓	✓	✓

Notes: This table shows origin-level SSIV coefficients of stacked long differences in log earnings and in the employment rate. The long difference are calculated from 1996-2001 and from 2001-2009. The instrument is the predicted migration accumulated in the same periods, measured as a fraction of the 1991 working-age native population. All regressions include time dummies and destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. All regressions are weighted by the working-age native population in 1991. Standard errors clustered at the origin municipality level in parenthesis. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 13: **Long run impacts: nonwage benefits**

	(1)	(2)	(3)
	Food	Transport	Health
Migrant inflow	-0.112 (0.124)	-0.753*** (0.088)	-0.384*** (0.068)
Observations	1,910	1,910	1,910
Municipalities	955	955	955
Time dummies	✓	✓	✓
Baseline × time	✓	✓	✓

Notes: This table shows origin-level SSIV coefficients of stacked long differences in in the proportion of native formal workers receiving nonwage benefits. The long difference are calculated from 1996-2001 and from 2001-2009. The instrument is the predicted migration accumulated in the same periods, measured as a fraction of the 1991 working-age native population. All regressions include time dummies and destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. All regressions are weighted by the working-age native population in 1991. Standard errors clustered at the origin municipality level in parenthesis. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 14: **Correlation between predicted migration from the Semiarid and other regions**

	(1)	(2)
	Migrant inflow from other regions	
Predicted inflow	0.080 (2.847)	0.081 (2.848)
Observations	8,190	8,190
Municipalities	684	684
Municipality dummies	✓	✓
Time dummies	✓	✓
Baseline \times time		✓

Notes: This table shows destination-level regression coefficients of the observed inflow of migrants from other regions on the predicted number of migrants from the Semiarid, both measured as a fraction of the working-age native population in 1991. All regressions include municipality and time dummies. Column (2) controls for destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. All regressions are weighted by the working-age native population in 1991. Standard errors clustered at the destination municipality-level in parenthesis. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table 15: **Effects on migration outflows of natives**

	(1)	(2)	(3)	(4)
Panel A. Low-educated				
Predicted inflow	1.352 (0.822)	1.273 (0.775)		
Lagged pred. inflow			-0.586 (0.615)	-0.342 (0.450)
Observations	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684
Panel B. High-educated				
Predicted inflow	0.151 (0.746)	0.109 (0.750)		
Lagged pred. inflow			0.871 (1.186)	0.466 (0.838)
Observations	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684
Municipality dummies	✓	✓	✓	✓
Time dummies	✓	✓	✓	✓
Baseline × time		✓		✓

Notes: This table shows regression coefficients of the number of people leaving the destination areas against the predicted number of migrants from the Semiarid region at the origin municipality level, both measured as a fraction of the native working-age population in 1991. In Columns (1)-(2) the regressor is the contemporaneous predicted migrant flow while in Columns (3)-(4) is the same variable lagged one year. All specifications include municipality and time dummies and are weighted by the 1991 native population. Columns (2) and (4) also control for destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. Standard errors clustered at the destination municipality-level in parenthesis. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

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

Raphael Corbi, Tiago Ferraz, and Renata Narita

ONLINE APPENDIX

Appendix A A Simple Model with Informality

In interpreting our findings, we develop a simple extension of a model with informality in which the formal sector has minimum wage but offer nonwage benefits that are frequently observed in the data (e.g. employer-provided health insurance). We follow an extension of the labor market model developed by [Harris and Todaro \(1970\)](#) provided in [Almeida and Carneiro \(2012\)](#). In their model minimum wage and labor legislation are the main institutions behind the existence of a formal and an informal sector. We add nonwage benefits in the formal sector as a source of adjustment of total compensation in the presence of binding minimum wages. We abstract from other sources of frictions, which is explored in much recent work on models of the labor market with monopsony to study immigration effects (e.g. [Amior and Manning \(2020\)](#) and [Amior and Stuhler \(2022\)](#)). They are not needed to understand the mechanism we emphasize, so we proceed with the following model.

Suppose an aggregate output function that combines both formal and informal labor inputs:

$$Y = f(L_f^d, L_i^d, \bar{K}) \quad (\text{A1})$$

where L_f^d and L_i^d are total formal and informal labor, respectively, required to production and \bar{K} the fixed capital stock. $f_{L_f^d L_i^d} \neq 0$ captures production linkages. The wage or the value of a job in the formal and informal sector are determined by marginal products in each sector, i.e.

$$W_i = \frac{\partial f}{\partial L_i^d} \quad (\text{A2})$$

$$W_f + (1 - t)B = \frac{\partial f}{\partial L_f^d} \geq \underline{W}_f + (1 - t)B \quad (\text{A3})$$

which yield labor demand equations assuming that the minimum wage is binding while nonwage benefits can be optimally chosen in the formal sector.

The labor market with two sectors at the destination can be represented by the following equations:

Formal labor demand	$L_f^d = a - b(\underline{W}_f + (1 - t)B) + cW_i$
Informal labor demand	$L_i^d = d - eW_i + f(\underline{W}_f + (1 - t)B)$
Formal labor supply	$L_f^s = g + h(\underline{W}_f + vB)(1 - U) - iW_i$
Informal labor supply	$L_i^s = j + kW_i - l(\underline{W}_f + vB)(1 - U)$
Equilibrium	$L_f^d = L_f^s(1 - U) = L_f^*$; $L_i^d = L_i^s = L_i^*$
Labor constraint	$L_f^s + L_i^s + O = M$

where W_f and W_i denote wages in the formal and informal sector, respectively. B are nonwage benefits offered in the formal sector only. For simplicity, we also do not

consider labor taxes or enforcement costs since this is not central in this paper. With the exception of the intercepts of the equations, we assume that all parameters are positive also implying that the two types of labor (formal and informal) are substitutes ($f_{L_f^d L_i^d} < 0$). Employers hiring formal workers can offer benefits (e.g. health insurance and food subsidies) at a cost that is below the wage cost ($t \leq 1$). We assume that workers value such benefits at the rate v , which can be smaller, equal or even larger than 1. The total number of individuals in the economy is M (natives plus migrants), who can either work or search for a job in the formal sector (L_f^s), work in the informal sector (L_i^s), or be out of the labor force (O). Labor markets are competitive, and equilibrium wages and quantities of labor in each sector are determined by the intersection of supply and demand.

We solve for L_f^* , L_i^* , W_i , B and U . The solution to this system is complex so we provide a numerical solution, given the above parametrization. The details on the construction of our numerical example are described in the footnote below.³¹

In our model we consider that migration exogenously shifts the supply of workers to the informal and formal sectors. Suppose an equal increase of 1p.p. in the parameters g and j (intercept shifters), so that the total labor force M increases by 2p.p.

Table A1: Effects of introducing migration in a labor market with informality

	(1)	(2)	(3)	(4)	(5)	(6)
	Benchmark	w/ Migration	Lower linkages	w/ Migration	Lower linkages and $B = 0$	w/ Migration
L_f^*	100	100.0	80.0	80.0	84.4	83.6
L_i^*	100	101.4	88.5	90.5	87.0	88.9
W_i	100	99.0	94.1	92.8	94.1	93.1
B	100	90.9	36.4	27.3	0.0	0.0
U	100	116.7	166.7	183.3	116.7	150.0

Table A1 shows the effects of migration on equilibrium allocations in the baseline economy given the above parameters and under two different scenarios: (i) with lower linkages in production across sectors ($c = f = 0.4$) and (ii) consisting of (i) plus absent nonwage benefits, which we introduce by setting B equal to 0. Baseline allocations in column (1) are normalized to 100.

Columns (3) and (5) show how the baseline equilibrium changes if we lower labor demand linkages across sectors with or without nonwage benefits. With endogenous nonwage benefits, column (3) shows that lower linkages reduce nonwage benefits to formal sector workers and decrease formal employment, thus raising unemployment. Likewise, lower linkages drop wages and employment in the informal sector. By remov-

³¹We set $a = d = 1, g = j = 0, b = e = h = k = 1$ and $c = f = i = l = 0.5$. The slope restrictions are consistent with integrated formal and informal sectors but we do consider that own effects are likely larger than cross-effects determining demand and supply of labor in each sector. We also consider that offering benefits is 50% cheaper to firms consistent with fiscal exemptions on such benefits ($t = 0.5$) and that workers value nonwage benefits less than wages with $v = 0.5$, motivated by lack of liquidity or pensions accumulation. Finally, given the above parametrization, we set the minimum wage \underline{W}_f at 1, $O = 0$ and $M = 1$.

ing nonwage benefits from the economy with lower linkages in column (5), the new equilibrium without this margin of adjustment is also consistent with more unemployment as suggested by Figure 2 (in Section 2.3) due to wage rigidity, and lower wages and employment in the informal sector than in the benchmark economy.

In columns (2), (4) and (6) we show the effects of introducing migration in each of these scenarios. In the benchmark economy with high production linkages across sectors and varying benefits (column (2)), migration increases unemployment and informal employment, and drops nonwage benefits and informal sector wages. Formal employment is unchanged. Under lower linkages, column (4) shows that the qualitative results are kept. However, migration induces a larger fall in informal sector wages and formal sector benefits in such context. Without nonwage benefits, the results in column (6) show that migration has now a negative impact on formal employment, as expected since formal firms cannot adjust benefits after the supply shock from migration. Consequently, unemployment also increases relatively more in this economy.

Appendix B 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.

B.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.

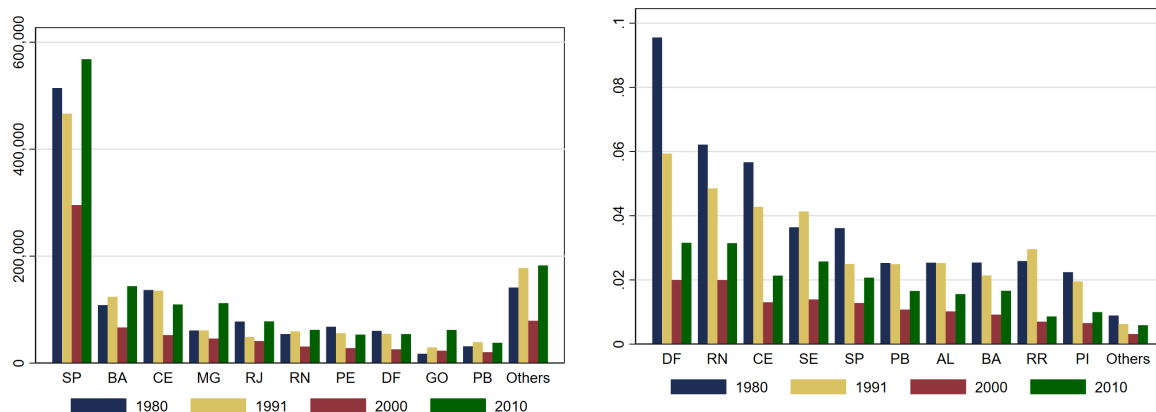
First, in the 2010 Census respondents were asked for how many years they had lived in the current municipality (from one up to ten). With this variable we are able to calculate the year when the individual have migrated. We consider migrant an individual who moved to the current municipality in the previous 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 B1 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.

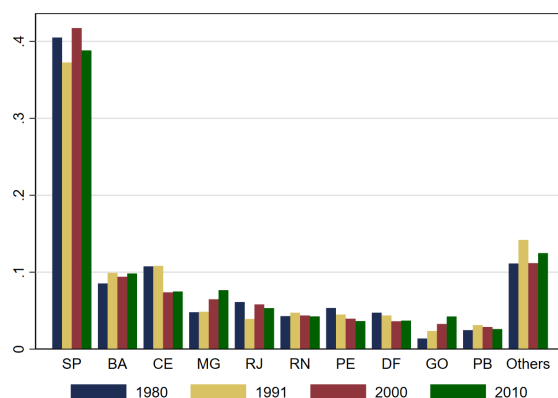
Table 3 compares migrants to low and high education natives. Migrants are slightly more educated and earn slightly less than low educated natives. They also have similar likelihood of working part time and being in the formal sector when compared to low education natives. On the other hand, high education natives are more likely to work in the formal sector, and have considerably higher pay. Table B2 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 B3).

Figure B1: Top destinations for migrants from the Semi-arid region



(a) Absolute number of Semi-arid's migrants

(b) Semi-arid's migrants as a fraction of total population



(c) Semi-arid's migrants as share of total migration

Notes: This figure presents the main destination states chosen by migrants from the Semi-arid region. Panel (a) shows the absolute number of migrants leaving the Semi-arid region to non-Semi-arid 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 B2: Main occupations for employed people: Migrants vs Natives

	Position	Occupation	Share of em- ployment	Cumulative
<i>Migrants</i>	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
<i>Low-ed. natives</i>	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
<i>High-ed. natives</i>	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 B3: **Main industries for employed people: Migrants vs Natives**

	Position	Industry	Share of em- ployed	Cumulative
<i>Migrants</i>	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
<i>Low-ed. natives</i>	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
<i>High-ed. natives</i>	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 C Weather shocks and predicted migration

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.

C.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 Antarctica) from 1901 to 2018. The grid resolution is $0.25^\circ \times 0.25^\circ$ (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 georeference 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 its centroid and calculate the average level of precipitation and temperature from these 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

$$Rainfall_{ot} = \ln \left(\sum_{\tau \in \{GS\}} r_{ort} \right) - \ln(\bar{r}_o) \quad (C1)$$

where r_{ort} 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 C1).

C.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 C1: Migration outflows induced by weather shocks (12 months)

	(1)	(2)	(3)	(4)	(5)	(6)
ainfall_{t-1}	-0.126*** (0.033)	-0.107*** (0.033)	-0.111*** (0.034)	-0.117*** (0.034)	-0.112*** (0.033)	-0.109*** (0.033)
Rainfall_t			-0.015 (0.039)	-0.029 (0.041)	-0.014 (0.039)	
Rainfall_{t-2}			0.037 (0.038)	0.059 (0.039)		
Rainfall_{t-3}				0.047 (0.033)		
Rainfall_{t+1}						-0.068* (0.037)
Observations	14,400	14,400	14,400	14,400	14,400	14,400
Municipalities	960	960	960	960	960	960
R-Squared	0.461	0.465	0.465	0.466	0.465	0.466
F Stat	7.907	3.801	3.234	3.270	3.492	3.615
Time dummies	✓	✓	✓	✓	✓	✓
Municipality dummies	✓	✓	✓	✓	✓	✓
Temperature shocks	✓	✓	✓	✓	✓	✓
Baseline \times time		✓	✓	✓	✓	✓

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) control for municipality-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. 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 ($0.25^\circ \times 0.25^\circ$) 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:

$$AI_{mt} = \frac{\sum_{\tau \in \{GS\}} PE_{m\tau t}}{\sum_{\tau \in \{GS\}} Pr_{m\tau t}} \quad (C2)$$

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 the aridity index z-score as

$$Z_{mt}^{AI} = \frac{(AI_{mt} - \overline{AI})}{AI_{sd}} \quad (C3)$$

We show in [Table C2](#) 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 C2: 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*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	
Aridity Index _{t-1}		0.003*** (0.001)	0.003*** (0.001)	0.003*** (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)		
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	✓	✓	✓	✓	✓	✓	✓
Baseline × time						✓	

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 controls for municipality-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. 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 D Shift-share instrument (SSIV)

In this section we derive the origin-level SSIV estimator, present and discuss the identifying assumptions needed to produce a consistent estimator of the effects of the inflow of migrants from the Semiarid region on labor markets in the destination municipalities.

We start from the structural equation 1. To simplify notation we omit the time subscript t . By the Frisch-Waugh-Lovell Theorem we can re-write it as

$$y_d^\perp = \beta m_d^\perp + \varepsilon_d^\perp \quad (\text{D1})$$

where all y_d^\perp is the vector of outcomes, m_d^\perp ³² is the observed number of Semiarid's migrants who entered the destination municipality d and ε_d^\perp is an structural residual. All variables are residualized to remove the effects from the controls.

In equation 4 we defined the shift-share instrumental variable (SSIV) as

$$\widehat{m}_d = \sum_{o=1}^O s_{od} \frac{\widehat{M}_o}{P_d} \quad (\text{D2})$$

where s_{od} is the share of migrants from origin municipality o who lived in the destination area d in 1991 and \widehat{M}_o is the predicted number of migrants leaving the Semiarid region driven by weather shocks.³³

The more traditional approach would be estimate β using \widehat{m}_d as instrument for the endogenous migrant inflow m_d^\perp . In such case we would have

$$\widehat{\beta} = \frac{\sum_d \widehat{m}_d y_d^\perp}{\sum_d \widehat{m}_d m_d^\perp} \quad (\text{D3})$$

By the definition of \widehat{m}_d in equation D2 and switching the order of the summation,

$$\widehat{\beta} = \frac{\sum_d \left(\sum_o s_{od} \frac{\widehat{M}_o}{P_d} \right) y_d^\perp}{\sum_d \left(\sum_o s_{od} \frac{\widehat{M}_o}{P_d} \right) m_d^\perp} = \frac{\sum_o \widehat{M}_o \left(\sum_d s_{od} \frac{y_d^\perp}{P_d} \right)}{\sum_o \widehat{M}_o \left(\sum_d s_{od} \frac{m_d^\perp}{P_d} \right)} = \frac{\sum_o s_o \widehat{M}_o \bar{y}_o}{\sum_o s_o \widehat{M}_o \bar{m}_o} \quad (\text{D4})$$

where $\bar{y}_o = \frac{\sum_d s_{od} \frac{y_d^\perp}{P_d}}{\sum_d s_{od}}$ is a weighted average of the residualized outcome, normalized by the population, which uses as weights the destination's average exposure to the shocks $s_o = \sum_d s_{od}$. The same result is valid for the endogenous variable m_d^\perp , meaning that we can estimate the following IV regression at the origin municipality-level:

$$\bar{y}_o = \beta \bar{m}_o + \bar{\varepsilon}_o \quad (\text{D5})$$

³²In order to facilitate the interpretation of the coefficients we normalize this measure dividing by the working-age native population in 1991, which means $m_d = \frac{M_d}{P_d}$

³³The same normalization is applied in the predicted inflow.

using the predicted number of migrants from the Semiarid region, \widehat{M}_o , as instrumental variable and weighting by the average exposure s_o .

This derivation is almost identical to that presented by [Borusyak et al. \(2021\)](#), except for the fact that we need to divide both variables by the predetermined population. But, this is only a normalization using the destination's native population and the equivalence result shows that the parameter β can be estimated at the level of the identifying variation, which in our case is the origin municipality hit by weather shocks.

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*): $\mathbb{E}[\sum_o s_o^2] \rightarrow 0$ 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 $s = \{s_o\}_o$.³⁴ 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 [Table D3](#) we present the effective sample size, which is calculated as the inverse of the Herfindahl concentration of migrants, $H = \frac{1}{\sum_o s_o^2}$. The large estimate reassures us that exposure concentration is not a relevant issue in our setting. [Appendix E](#) presents evidence that we may assume that the shocks we are using can be treated as uncorrelated.

³⁴As 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 1](#) computed at the level of shocks (e.g. municipality of origin).

Table D3: **SSIV First Stage**

	(1)	(2)	(3)
First stage coefficient	0.912*** (0.015)	0.910*** (0.015)	0.925*** (0.019)
F-statistic	3,462	3,464	2,275
Observations	11,460	11,460	11,460
Municipalities	955	955	955
Effective sample size	7,301	7,301	7,301
Time dummies		✓	✓
Baseline × time			✓

Notes: This table shows the SSIV first stage coefficients of the origin-level weighted average of the endogenous inflow of migrants at the destinations against the predicted number of migrants from the Semiarid region. Each observation is a municipality of origin by year cell. The F-statistic is calculated as the square of the coefficient t-statistic (see [Borusyak et al., 2021](#)). The effective sample size is the inverse of the HHI of the origin-level exposure. Column (2) include time dummies while Column (3) also controls for destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. Regressions are weighted by the average destination exposure to the past settlement of migrants from the origin municipality. Standard errors cluster by municipality of origin in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Appendix E Spatial correlation in weather shocks

Weather events are likely correlated across space. Figure 12 shows that precipitation levels in the Semi-arid are similar among nearby municipalities. Potentially this could invalidate the consistency of our estimator given by *Assumption 2 (Many uncorrelated shocks)* discussed in Appendix D. 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.³⁵ Brazil has 5,565 municipalities, 361 micro and 87 mesoregions overall. The Semi-arid 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 E2 displays Moran’s index of spatial auto-correlation of rainfall shocks for each of the three geographic aggregates in columns 1-3.³⁶ 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 E2 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 E3-E5 show that our results associating migration and earnings, employment and nonwage benefits are very similar to the municipality-level estimates, although standard errors increase substantially, as one would expect considering that there are fewer units from which we can leverage variation. All those results indicate that spatial correlation among rainfall shocks in origin municipalities are not a source of relevant bias in our setting.

³⁵Table E1 reports summary statistics of our main variables for all both levels of aggregation.

³⁶Moran’s I is calculated according to the following formula:

$$I = \frac{1}{\sum_i \sum_j w_{ij}} \times \frac{\sum_i \sum_j w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\frac{1}{N} (y_i - \bar{y})^2} \quad (E1)$$

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 E1: **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 km².

Table E2: **Migration outflows induced by weather shocks according to different aggregation levels**

	(1)	(2)	(3)
	Municipality	Micro-region	Meso-region
Rainfall _{<i>t</i>-1}	-0.099*** (0.028)	-0.094*** (0.032)	-0.099*** (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 E3: **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	-0.869*** (0.197)	-0.846*** (0.302)	-0.871 (0.550)
Observations	11,460	1,644	420
Regions	955	137	35
B. Change in log earnings, formal sector			
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.593*** (0.198)	-0.558* (0.290)	-0.556 (0.527)
Observations	11,460	1,644	420
Regions	955	137	35
C. Change in log earnings, informal sector			
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.746*** (0.123)	-0.745*** (0.201)	-0.769** (0.343)
Observations	11,460	1,644	420
Regions	955	137	35
Demographics	✓	✓	✓
Time dummies	✓	✓	✓

Notes: This table origin-level SSIV coefficients on changes in log earnings, by sector. Each observation is a municipality-year cell. Informal sector also includes self-employed workers. All specifications include time and control for destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and older than 65; share of non-white population; share of population with college education; share of women in the total and employed populations; shares of employment in agriculture and manufacturing; logs of the average household income and size; and the shares of households with access to electricity and piped water) interacted with time dummies. 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 regressions are weighted by the average exposure of each destination to the past settlement of migrants from the respective origin region. Standard errors clustered at the respective aggregation level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table E4: 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	-0.018 (0.034)	-0.003 (0.058)	0.007 (0.091)
Observations	11,460	1,644	420
Regions	955	137	35
B. Change in formal employment rate			
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.126*** (0.037)	-0.117** (0.055)	-0.125 (0.098)
Observations	11,460	1,644	420
Regions	955	137	35
C. Change in informal employment rate			
	Municipality	Micro-region	Meso-region
Predicted inflow	0.108*** (0.034)	0.114** (0.057)	0.133 (0.095)
Observations	11,460	1,644	420
Regions	955	137	35
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 E5: Effects of migration on nonwage benefits according to different aggregation levels

	(1)	(2)	(3)
A. Food			
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.687*** (0.086)	-0.658*** (0.134)	-0.688*** (0.216)
Observations	11,460	1,644	420
Regions	955	137	35
B. Transport			
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.372*** (0.062)	-0.305*** (0.104)	-0.290* (0.157)
Observations	11,460	1,644	420
Regions	955	137	35
C. Health			
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.315*** (0.064)	-0.289*** (0.097)	-0.312* (0.173)
Observations	11,460	1,644	420
Regions	955	137	35
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%.