Internal Migration and Labor Market Adjustments in the Presence of Non-wage Compensation

Raphael Corbi[*] Tiago Ferraz[†] Renata Narita[‡]

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Abstract

In this paper, we argue that adjustments in non-wage compensation are empirically relevant and thus can have important implications for studying the effects of labor supply shocks. We investigate the labor market impacts of internal migration in Brazil using a shift-share approach that combines weather-induced migration with past settlement patterns in each destination. Increasing migration inflows reduces formal employment and increases informal jobs by a similar magnitude. Consistent with downward wage rigidity, we find a weaker negative effect on formal earnings than on informal and a negative impact on the share of workers receiving non-wage benefits. Less educated individuals bear most of these costs. Unemployment and labor force participation increase, mainly driven by non-head members of the household. We interpret our findings within a simple model with two sectors in an economy with different levels of intersectoral linkages and with flexible or fixed benefits that generates predictions broadly consistent with our findings.

Keywords: Internal migration, wages, employment, non-wage benefits.
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[*]University of São Paulo, Department of Economics, Email: rcorbi@usp.br
[†]University of São Paulo, Department of Economics, Email: tiago.ferraz@usp.br
[‡]University of São Paulo, Department of Economics, Email: rnarita@usp.br
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1 Introduction

Migration, both within and beyond borders, has important implications in terms of development, demographic and economic dynamics. As a response, a large literature has emerged on the impacts of migration on the native population, particularly 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 growing fraction of scholars has concluded that migration may have 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 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 non-wage aspects of jobs are fixed. Allowing for adjustments along these margins may have important implications for the study of labor markets. Clemens (2021) argues they may explain existing controversies over the economics of minimum wages. Less is known about the role of non-wage adjustments in our understanding of the consequences of migration.

In this paper we argue that adjustments in non-wage compensation are empirically relevant and thus can have important implications for studying the effects of labor supply shocks due to migration. In particular, we study the impacts of internal migration in Brazil on the labor market outcomes of natives in a setting where downward wage rigidity is present, non-wage benefits are a significant 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 non-wage benefits of formal jobs or simply lowering salaries in unregulated informal markets.

The theory is based on a simple model that generates predictions for the impact of migration on labor markets with two sectors in an economy with different levels of intersectoral linkages and with endogenous or fixed benefits. From low to medium level of linkages, the impact of migration in terms of employment and wage drops in magnitude. Allowing firms to adjust benefits as a response to shocks also softens the impact on employment. Non-wage benefits are a relevant margin of adjustment for firms, especially in more regulated labor markets. They ease constraints and allow employers to partially absorb shocks.

Brazil provides a good environment for our investigation for three reasons. First, over 3 million people in the Brazilian Semiarid, a historical source of climate migrants, left their hometowns during our sample period of 1996-2010. Second, a within-country analysis minimizes econometric concerns about allocating migrants to particular skill groups (Dustmann et al., 2012). Third, over 40 percent of workers are employed in the less frictional informal labor sector, where firms do not comply with labor market statutes, such as minimum wage laws and firing regulations. The rest of the workforce participates in the formal sector where minimum wage is binding (above 70% of the median wage) and non-wage 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 non-wage benefits, changes in this margin of adjustment can have important welfare implications.

To address the econometric concerns associated with the fact that migrants tend to move to areas with better labor market opportunities, we take advantage of a recent body of work that provides a clear framework for distinguishing sufficient conditions for identification and properly computing standard errors (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2021; Jaeger et al., 2018; Adao et al., 2019). In particular, 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 $0.13p.p.$, while increases the number of informal[2] jobs by $0.11p.p.$. 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 downward, 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, we find a decrease between 0.59% and 1.00% on average earnings in the formal sector and a negative impact on the share of formal workers receiving employer-provided health insurance in the range of $0.31p.p.$ to $0.47p.p.$, food vouchers from $0.33p.p.$ to $0.69.p.$ and transportation subsidies from $0.37p.p.$ to $0.57p.p.$

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

[2] Our definition of informal sector also includes self-employed workers.

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 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 drops.[3] Wages in the formal sector reduce across the entire wage distribution but more so for higher wage percentiles which is consistent with 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 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 non-wage 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 unemployment and labor force participation increases by roughly $0.07 - 0.09 p.p.$, which may seem at odds with previous results since earnings fall in the informal sector and benefits drop 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 the head of household 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 non-wage 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)

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

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

natives respond to the adverse effects by moving to markets that were not directly targeted by migrant arrivals.

Our work is related to a broad 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,[5] 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). Some of these studies find that the wages of natives are harmed by immigration (Borjas and Monras, 2017), while others find only a minor negative effect on native wages (Card, 2001), or even positive (Ottaviano et al., 2013; Foged and Peri, 2016; Azoulay et al., 2022).[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 fourfold. First, we show that firms systematically adjust non-wage benefits in response to labor supply shocks. Second, accounting for such adjustments are key to understanding the effects of migration on natives. Third, 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. Fourth, we add to a growing body of evidence that migration is a relevant coping mechanism against climate change, especially for vulnerable populations in rural areas of developing countries (Skoufias et al., 2013; Assunção and Chein, 2016).

Non-wage 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 non-wage components when facing adverse economic shocks (Babecký et al., 2019) or as an strategy to offset collective bargaining (Cardoso and Portugal, 2005), particularly when base wages are rigid (Babecký et al.,

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

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

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

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

2012). We add to this literature by showing that non-wage benefits are an important margin of adjustment in the case of labor supply shocks due to internal migration.

This paper is organized as follows. In the next section, we first present background information on the Brazilian Semiarid region and local labor markets. Section 3 outlines a simple framework for interpreting our findings. Section 4 describes the data and empirical framework, and reports first-stage estimates that link observed migration patterns to our predicted migration flows. Next, we present and analyze the main results on employment, wages and non-wage wage benefits in Section 5. We also study the sensitivity and heterogeneity of our main estimates. Finally, we interpret our main estimates in light of our simple model and conclude.

2 Background

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

2.1 Brazilian Semiarid

The Brazilian Semiarid encompasses 960 municipalities spread over 9 states, covering an area of around 976,000km^2.[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 0.5[10]; (iii) risk of drought above 60%[11]. The average historical precipitation in the Semiarid is about 780mm, as opposed to around 1,600 mm for the rest of the country[12], 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

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

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

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

[12]See Figure 11.

to a national average of 25% and 15 per 1000 births, respectively (Rocha and Soares, 2015). More than 80% of the adult population had less than 8 years of schooling in 1991.

Such poor socioeconomic indicators associated with periods of extreme drought have historically driven large outflows of migrants - or so-called *retirantes* - from the Semiarid to other areas of the country (Barbieri et al., 2010). During the 1960s and 1970s, net migration out of Northeastern states (where most of the Semiarid is located) was 2,2 and 3,0 millions individuals (Carvalho and Garcia, 2002), which correspond to net migration rates of 7.6 and 8.7%, respectively. Between 1996 and 2010, around 3.0 million people left the Semiarid 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 Semiarid in the last four decades. However, in relative terms incoming migrants represented a population increase of above 2% for the top 10 receiving states.

2.2 Labor Markets in Brazil

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

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

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.

Non-wage compensation. 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 21% 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 non-wage 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.

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

3 A Simple Theory

In this section, we describe a simple model assuming perfectly competitive labor markets to guide our analysis. We assume migrants and natives to be perfect substitutes and investigate the consequences of a migration shock that shifts the aggregate labor supply to the right. Then we introduce intersectoral linkages where formal and informal workers are substitutes.

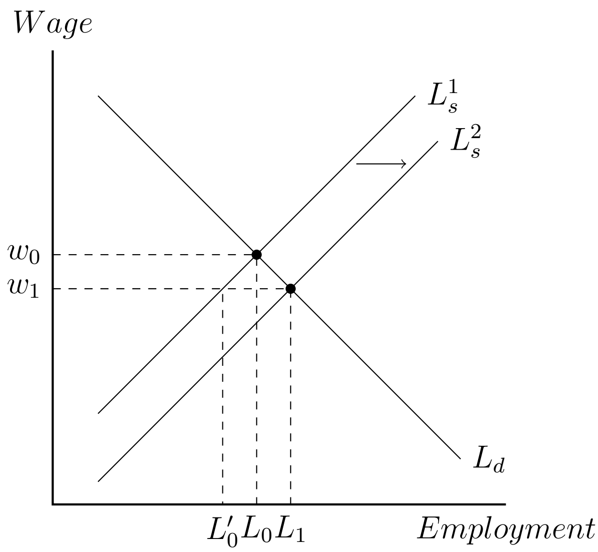
We begin by studying a case where institutions that may constrain labor market adjustment (e.g. minimum wages) are absent in the regulated sector and firm-provided non-wage job attributes are fixed. Figure 1 shows that labor supply elasticity determines the extent to which migration affects employment vis-à-vis wages. In the extreme case in which supply is inelastic, migration negatively affects wages with no effect on the employment of natives and absorbing all migrant workforce. On the other hand, with an elastic labor supply, the reduction in wages makes 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, downward wage rigidities are often present in reality due to minimum wage laws and collective bargaining agreements. In this case, migration shocks can be accommodated by job losses or lower labor costs, for example, reducing non-wage benefits (McKenzie, 1980; Clemens, 2021). Figure 2 illustrates this point. Starting with an economy where the minimum wage is set at the market-clearing level, a migration shock causes unemployment of L_1-L_0. The subsequent reduction in non-wage compensation will shift both the supply and demand curves. For firms, lowering non-wage benefits imply a higher labor demand curve because it increases its revenue net of costs. With wages fixed at $\underline{w}$, the new level of employment is L_2. For workers, under the assumption that they value such benefits, labor supply shifts upwards which is consistent with jobs becoming less attractive to workers and with a higher wage to compensate for the loss in benefits.

In this case, the shift of the supply curve due to adjustments in non-wage benefits may undo the migration supply shock and may even nullify its negative effect on employment. In this case, demand and supply shift due to a reduction in amenities bringing the economy to a new equilibrium that pays exactly the minimum wage and employment is at L_2, where there is no unemployment. While migration increases total employment from L_0 to L_2, some reduction of employment among natives may occur. Importantly, this reduction comes from some workers withdrawing from the labor market since they are not willing to work at the lower benefit level.

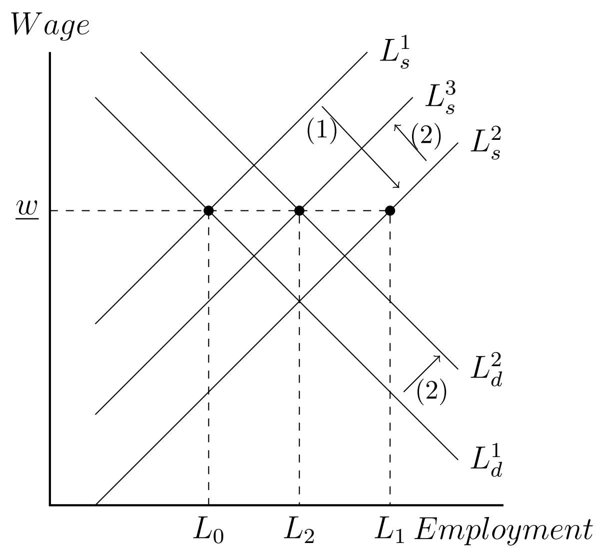
In sum, in a simple competitive model with no rigidities, which is likely closer to the informal (unregulated) sector case, we expect some negative effects on wages and an increase in total employment. The effects on employment of natives depend on the labor supply elasticity. As we expand this simple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

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



aspect that determines this result is the valuation of benefits by workers compared to the cost of providing such benefits by firms.

Figure 2: The Effects of Migration with Binding Minimum Wages and Perfect Adjustment of Non-wage Benefits



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

Empirically, these forces are likely to affect mainly those workers at the bottom/medium of the formal wage distribution since migrants are generally low skilled.[15] Low-skill workers receive disproportionately more generous benefits (e.g. health insurance and

[15]This follows the arguments developed by the labor market model in Card and Lemieux (2001) and Borjas (2003). In Section 4, we present descriptive evidence that supports greater substitutability between migrants and less skilled natives in the labor market.

food vouchers) but have wages that are more prone to be affected by minimum wage policies and collective bargaining agreements. Even if many firms employ both high and low-skilled workforce which may produce spillover effects due to complementarities, the impact on high-skilled workers are likely to be of second order.

Intersectoral linkages. So far, we have considered the formal and informal sectors as independent, which masks important intersectoral linkages, in particular, on the production side (see Ulyssea (2010, 2018) and Bosch and Esteban-Pretel (2012)). When the two types of labor are highly substitutes, informal employment and wages can compensate for wage rigidities in the formal sector. This should be particularly relevant to understanding the implications of an increase in migration in the labor market where formal wages are rigid thereby increasing the importance of the informal sector as an outside option.

We develop a simple extension of a model with informality in which the formal sector has minimum wage and offers non-wage benefits that are frequently observed in the data (such as health insurance and food subsidy). Our starting point is the seminal contribution of 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 non-wage benefits in the formal sector as a source of adjustment of total compensation in the presence of minimum wages.[16] Appendix A presents the model and here we summarize its main predictions.

In this model, the effects of migration may depend on the degree of substitution between formal and informal labor inputs in production and on the non-wage 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 non-wage benefits, and informal wages.

Table A1 simulates the impact of a migration shock when non-wage benefits are flexible (column 2) or fixed (column 3). It does so by assuming that production linkages are low, medium and high, in Panels A, B and C, respectively. In the benchmark economy with medium production linkages across sectors and flexible non-wage benefits, migration increases unemployment and informal employment but decreases non-wage benefits and informal sector wages. Formal employment remains unchanged. With non-wage benefits fixed at baseline levels, 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 and the informal sector adjust more. Under lower intersectoral linkages, the qualitative

[16]We abstract from other sources of labor market frictions, which are 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)). These 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.

results are the same with stronger effects in informal markets and formal sector benefits.

4 Data and Empirical Strategy

In this section we begin by listing the main sources of data used in our analysis and showing some descriptive statistics. Then we describe the empirical framework and report first-stage estimates that link observed migration patterns to our predicted migration flows.

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 out study.[17] 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. In Appendix B we provide more details on how we structure our yearly migration dataset.

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 $0.5° \times 0.5°$ 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.[18] We define the rainfall shocks as deviations from the historical average.[19]

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

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

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

[19] See Appendix C for a detailed description and discussion on this measure.

the Semiarid in order to minimize concerns about spatial correlation in weather shocks.

Our main outcomes come from data on earnings and indicators for employment; whether the worker is an employee in the formal sector (registered with the Ministry of Labor), informal sector or self-employed; whether she is unemployed or out of the labor force. We also create indicator variables for some forms of non-wage 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 and take averages at the municipality-year level. The final destination sample has 2,152,950 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 0.30 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).[20] Among workers employed in the formal sector, 39% receive financial help to cover expenses with food, 36% for transport and 21% for health expenditures.[21]

Finally, Table 3 compares migrants to low and high education natives. Migrants are slightly more educated and earn slightly less than less-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 B1 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 B2). Overall, this characterization is consistent with greater substitutability between migrants and less skilled natives in the labor market.

4.1 Empirical Strategy

Here 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. Next we

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

[21]Less than 1% of informal and self-employed workers receive any kind of non-wage compensation.

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.

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

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

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 rate[22] from origin municipality o in year t, using weather shocks in the previous year:

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

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:

$$\widehat{M}_{ot} = \widehat{m}_{ot} \times P_o \tag{3}$$

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

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

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

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

area d in 1991[23] and P_d is total population at d in 1991.[24] Thus our instrument $\widetilde{m}_{dt}$ 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.[25]

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

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

$$\Delta y_{dt} = \alpha + \beta \widetilde{m}_{dt} + \gamma \Delta X_{dt} + \psi_t + \epsilon_{dt} \tag{5}$$

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

$$\bar{y}_{ot} = \alpha + \beta \widehat{M}_{ot} + \bar{\varepsilon}_{ot} \tag{5'}$$

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

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

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

[25]Note 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.[26]

As expected, rainfall shocks in the previous year are negatively correlated with migration outflows indicating that Semiarid's inhabitants leave the region during drought periods. Coefficient estimates are remarkably stable across specifications and adding more lags 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 $1p.p.$ in migration outflow rate.

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

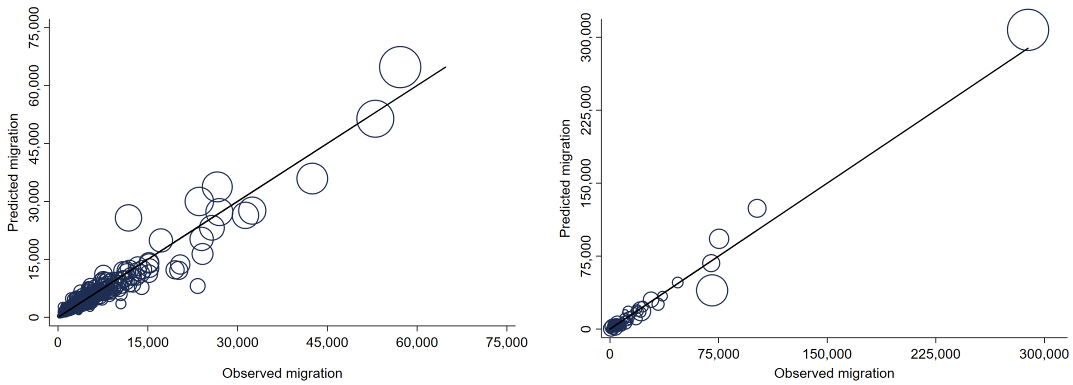
In Appendix C we describe in more detail our data source for weather shocks, discuss alternative measures of weather, and present further details about how we constructed our instrument including predicted and past settlement patterns.

Overall, this analysis shows that our strategy provides a strong first-stage as predicted migration rates, $\widetilde{m}_{dt}$, are strongly correlated with observed migration. Appendix Table D1 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.[27]

[26]Similar, but not identical, 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. Therefore, two municipalities inside the same grid have different shocks because the distance to the centroid is not the same.

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

Figure 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).

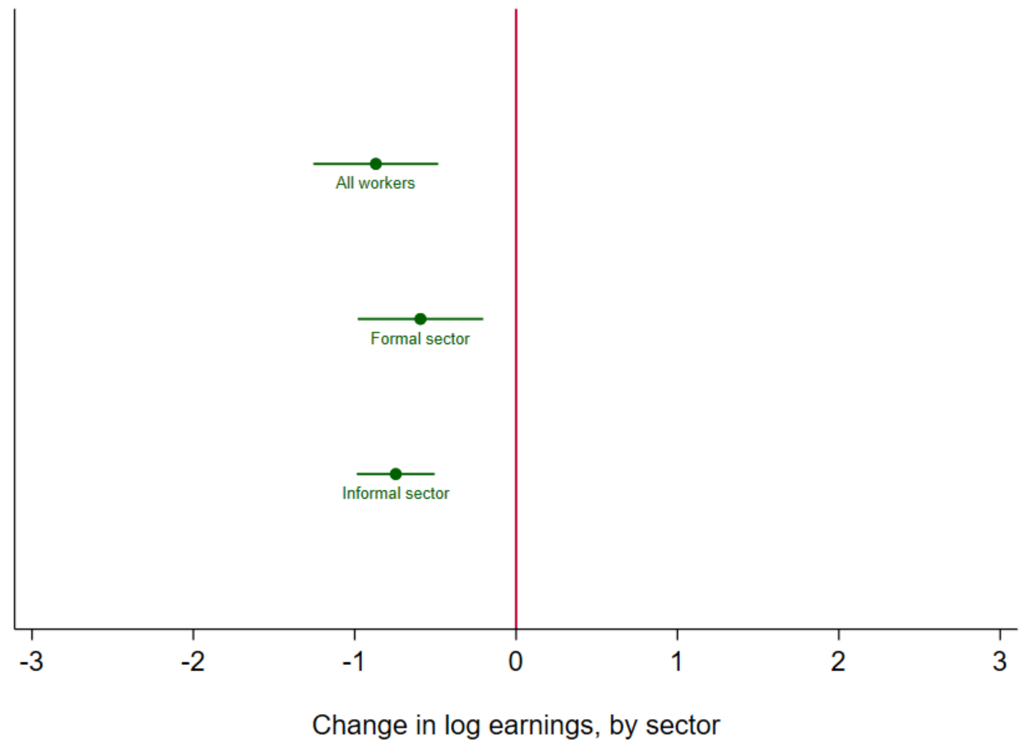
5 Labor Market Effects of Migration Inflows

Now we turn our attention to labor markets at the destination and investigate how migration inflows affect earnings, employment, unemployment, and labor force participation of native workers. Next, we explore how labor markets adjust to migration shocks in terms of non-wage compensation.

We begin by investigating how native workers' earnings adjust to exogenous migration inflows. Table 5 reports several specifications for our 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. Adding covariates lowers somewhat the magnitude of our estimates but does not change substantially our main conclusions. 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 0.75% for those employed in the informal sector.

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

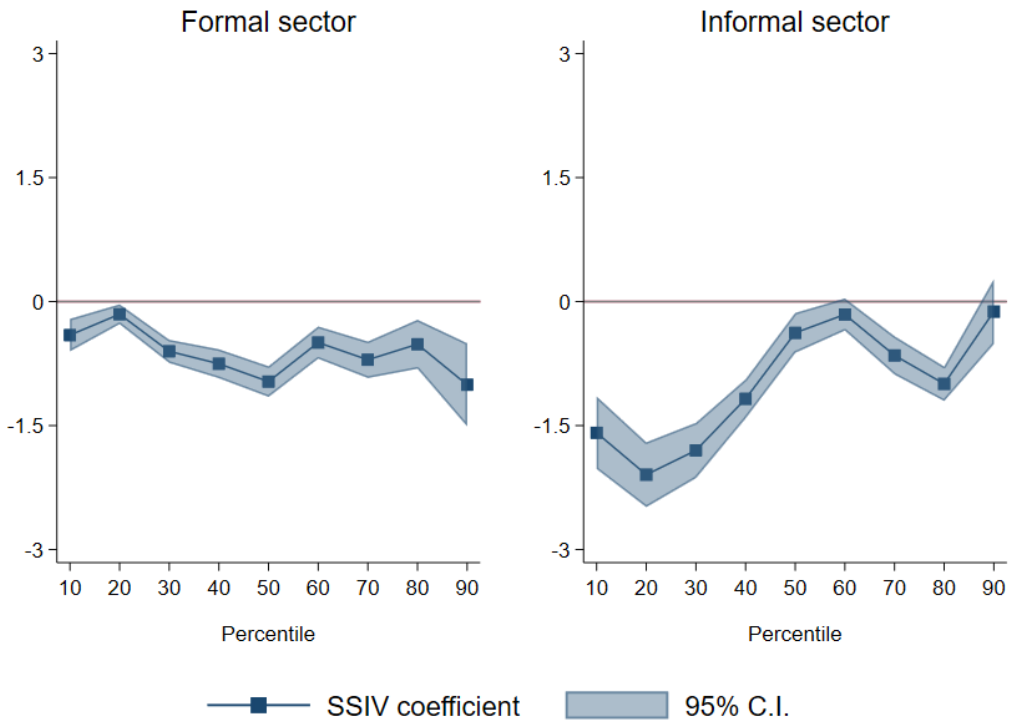


Notes: This figure plots origin-level SSIV coefficients on change in log earnings, by sector. Informal sector includes self-employed workers. Controls include time dummies and destination-level 1991 characteristics (log of working-age native population; shares of population aged 15-25, 26-50, 51-65 and 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.

Figure 4 summarizes our main findings. 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.

We also investigate the differential effects according to the native worker's position in the earnings distribution. Figure 5 reports estimates by earnings decile. For those workers employed in the formal sector, we find smaller impacts at the bottom of the distribution. This is consistent with wage rigidity in the formal sector which limits 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, may be attenuated due to some formal sector workers moving into informality or self-employment. As workers in the formal sector are more

Figure 5: Effects of predicted migration along the earnings distribution



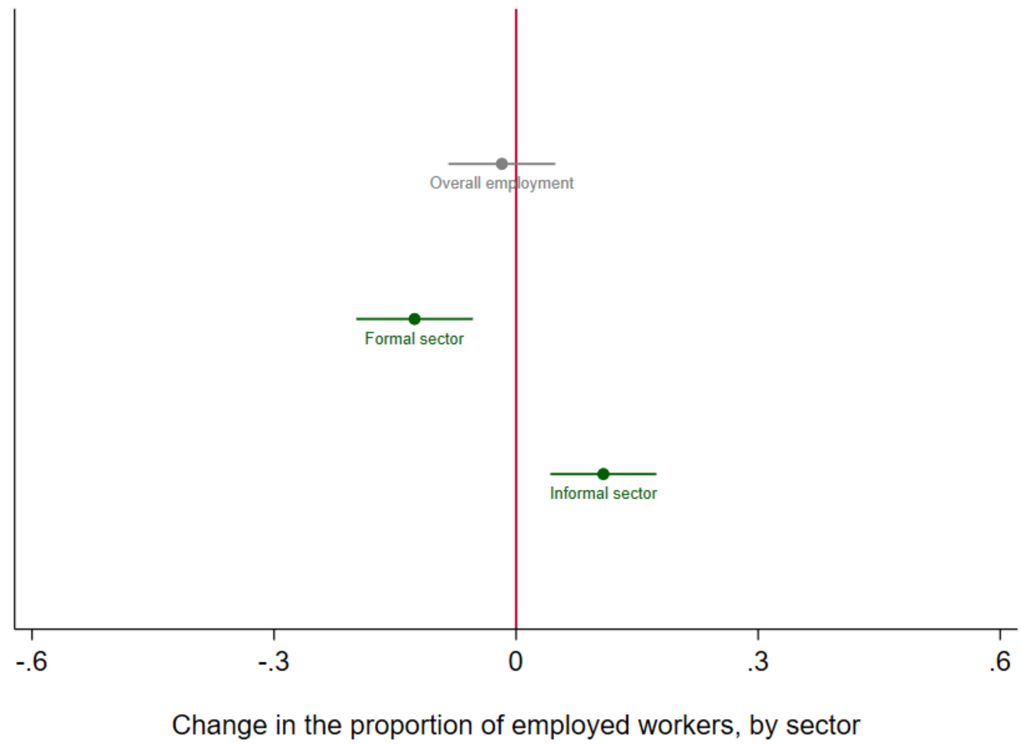
Notes: This figure plots SSIV coefficients of change in the average of log earnings, in each decile, by sector. Informal sector also includes self-employed workers. Controls include time dummies and destination-level 1991 characteristics (log of working-age native population; shares of population aged 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.

productive, on average, this increases earnings at higher percentiles in other sectors.

Our results for employment are summarized in Figure 6. While we find no effect on overall employment, the inflow of migrants from the Semiarid does change the composition of workers across sectors. Table 6 reports the point estimates across all specifications. Our estimates in Panels B and C imply that a one percentage point increase in the inflow reduces the share of formal employment by $0.13p.p.$, and increases the share of informal by almost the same amount ($0.11p.p.$).

To draw a more complete picture we also estimate the impacts on unemployment and labor force participation reported in Table 7. Migration inflows lead to an increase of $0.09p.p.$ in the unemployment rate and a decrease of $0.08p.p.$ in the proportion of out-of-labor-force individuals. What mechanism accounts for these estimates is ex-ante unclear. On one hand, increased competition in the labor market could discourage native individuals to work if wages or benefits fall, as predicted by the model developed in the Appendix A. On the other hand, if the primary earner in the household looses 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).

Figure 6: **Effects of internal migration on employment**



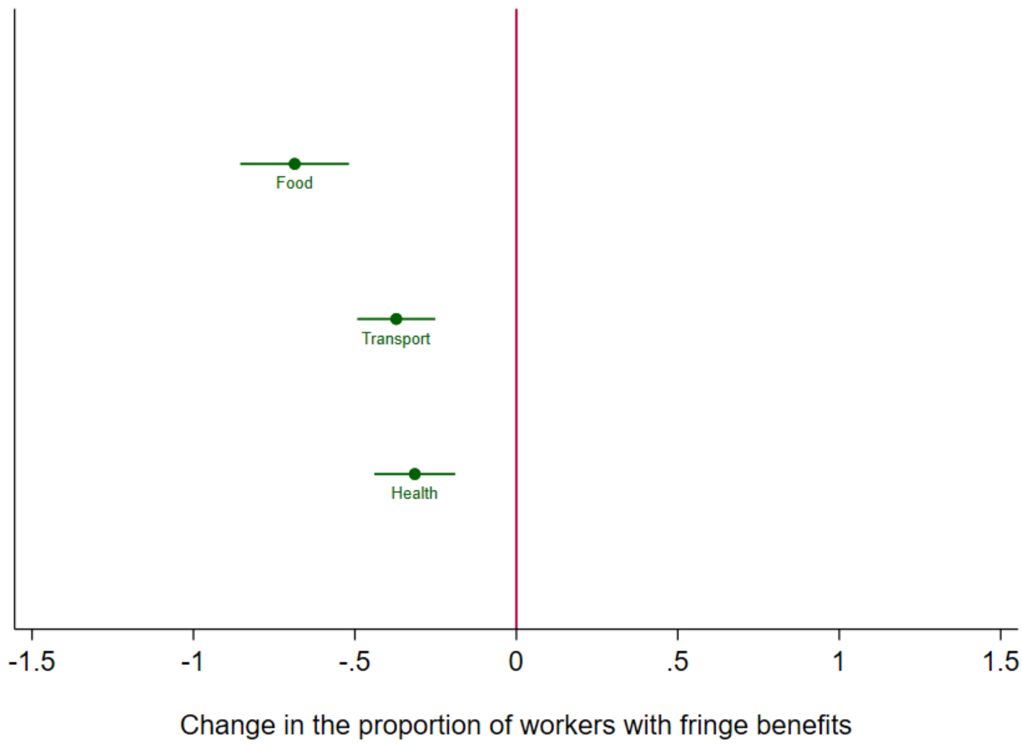
Notes: This figure plots origin-level SSIV coefficients of change in employment rate, by sector, measured as a fraction of the native working-age population in 1991. Informal sector includes self-employed workers. Controls include time dummies and destination-level 1991 characteristics (log of working-age 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.

We test this second mechanism by running the same regressions separately for individuals identified as head or non-head of the household. According to Table 8, almost all of the employment effects come from the head of households, while the changes in unemployment and inactivity rates stem from non-head members. That suggests that the second channel prevails. Also, the symmetry between the effects on unemployment and inactivity indicates that once secondary earners enter the market, it takes time for them to find a job.

5.1 Non-wage Compensation.

We now explore an additional margin of adjustment due to migration shocks. As firms operating in the formal sector cannot reduce wages below the legal minimum, they may adjust to labor supply shocks by reducing fringe benefits as discussed in Section 2.2. We focus on individuals who are currently holding a formal job because these benefits are almost exclusively offered by formal firms. Figure 7 reports the estimates. 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

Figure 7: **Effects of internal migration on non-wage 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.

$0.37p.p.$ to $0.52p.p.$, and health insurance in the range of $0.31p.p.$ to $0.47p.p.$. See Table 9 for the underlying point estimates.

Next we complement these estimates by focusing on the behavior of firms as providers of health insurance to their employees.[28] Instead of relying on survey data, here 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 $y_{idt} = \mathbb{1}\left(t \geq t^s\right)$ 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 municipality d

[28] 20% 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.

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

In column 1 of Table 10 we find that firms operating in a municipality that receives more incoming migrants are on average less likely to provide health insurance to employees.[29] An increase of one standard deviation in migration rate of 1p.p. reported in Table 1 implies a 1.5p.p. decrease in the share of firms that provide health insurance, roughly average of 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 of greater magnitude for larger firms. Firms above 100 employees are at least 6 times more likely to provide health insurance as part of compensation.

5.2 Sensitivity and Heterogeneity Analysis.

In this section, we summarize a series of robustness checks we have performed to assess the validity of our main findings. Then we study the heterogeneity of our main estimated effects with respect to workers' education level.

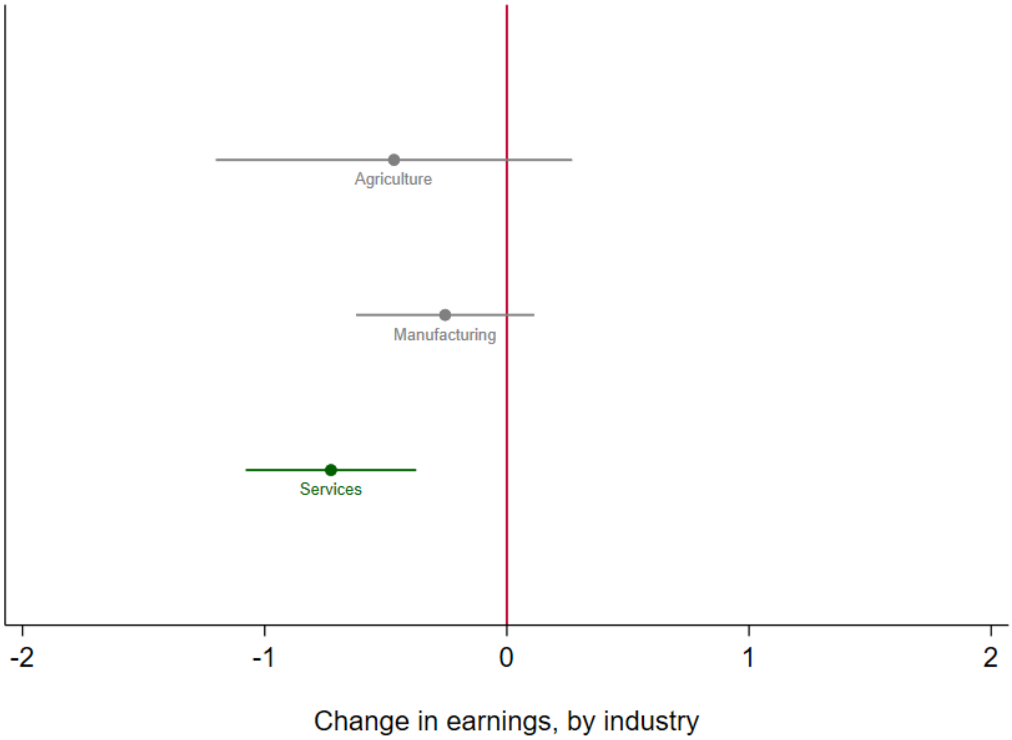
The first issue we address is whether a shift in local labor demand may be confounding our identification. If that was the case, then we should expect that migrants from other regions outside the Semiarid would be attracted for the same destinations. In other words, we should observe a positive correlation between migrant inflows from the Semiarid and that from other regions. In Table 11 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 summarize the effects from regressions of changes in log earnings on the predicted migrant inflow rate, separately by industry where the individual is employed. In Table 12 we report the detailed results. 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

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

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.

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 non-wage benefits remain virtually unchanged, indicating that spatial correlation among rainfall shocks in origin municipalities are irrelevant to our results.

Next we assess whether individuals with different levels of education may experience differential impacts. In particular, we expect that low-education native workers to be close substitutes to migrants. Thus we reestimate the effect of migration on local labor market outcomes of natives with low and high education, separately. We define as less educated those with up to 8 years of schooling, which is equivalent to complete

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

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

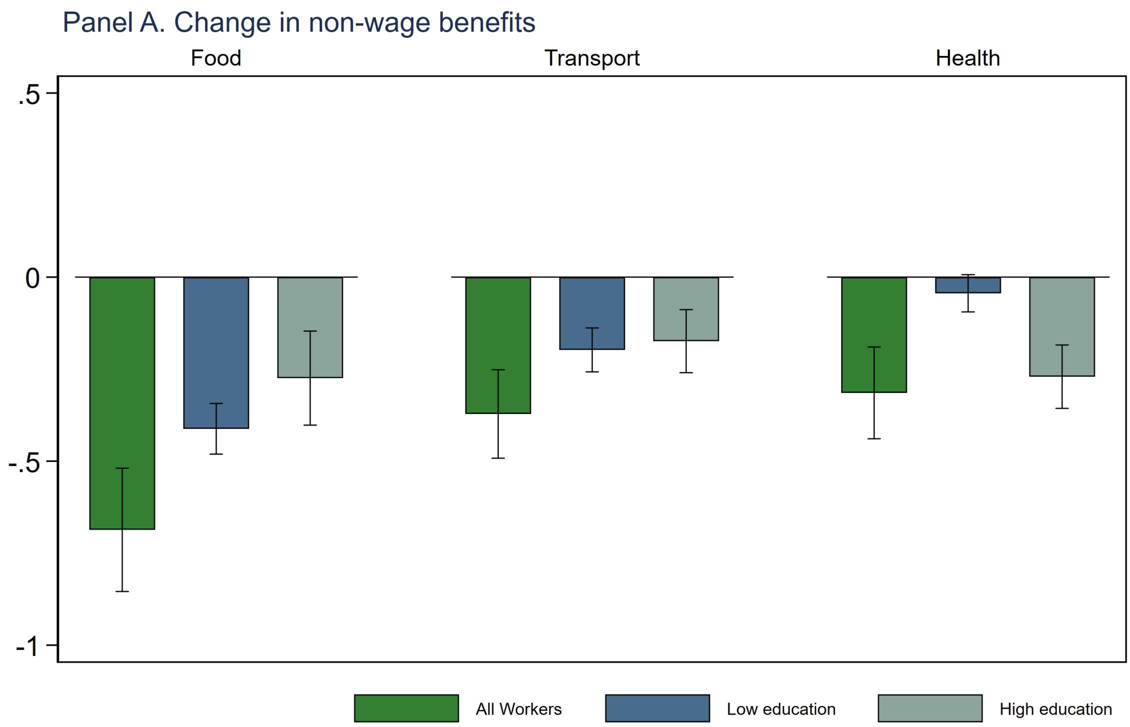
Notes: This figure plots SSIV coefficients of change in labor market outcomes, by education level. In Panel A, the dependent variables are the changes in employment rates while in Panel B we present estimates for changes in log earnings, for each sector. Each bar represents the SSIV coefficient for a 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.

elementary education. In our sample, 58% of natives are less 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 with 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 non-wage 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

Figure 10: **Effects of predicted migration on non-wage benefits, by education level**



Notes: This figure plots regression coefficients of change in non-wage benefits, by education level, against the predicted number of migrants from the Semiarid region in each destination municipality, measured as a fraction of the native working-age population in 1991. The dependent variables are the changes in the proportions of native workers in the formal sector who received some help to cover expenses with food, transport or health insurance. Each bar represents the reduced form coefficient by education level (low education = up to 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.

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 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.

5.3 Long Run Effects.

Here 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.[31] We stack the two periods and estimate the same origin-level SSIV regressions from Section 5.

Table 13 shows the long term effects of the inflow of migrants from the Semiarid 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 14 shows that non-wage 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 $0.75p.p$ 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 estimated, and the magnitude is greater for natives of lower education, who are the most affected by the arrivals of Semiarid migrants.

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

6 Discussion and Concluding Remarks

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.

Overall our results indicate that an exogenous supply shock of low-skill workers reduces earnings in the unregulated informal sector, especially at the bottom of the wage distribution. To a lesser extent, earnings also drop in the formal sector, with close to zero estimates at the bottom as minimum wage restrictions and collective agreements are more binding. Adjustments in nonwage benefits such as food vouchers, transportation subsidies, and health insurance compensate for these rigidities.

We also observe a decrease in the formal employment of natives due to wage rigidities and an imperfect adjustment of the benefit margin. In the informal sector, an increase in employment follows the large fall in earnings, consistent with workers reallocating from the formal to the informal sector or self-employment. Unemployment and labor force participation also increase, in part, due to non-head members of the households joining the job market in response to migration shocks.

As discussed in Section 3, our model generates predictions for the impact of migration on labor markets with two sectors in an economy with different levels of intersectoral linkages and with endogenous or fixed benefits. From low to medium level of linkages, the impact of migration in terms of employment and wage drops in magnitude. Allowing firms to adjust benefits as a response to shocks, also softens the impacts as expected. In summary, our estimates are broadly consistent with lower/medium levels of linkages and with imperfectly flexible benefits, as formal employment drops likely due to collective agreements over nonwage benefits.

Taking stock, our findings call attention to the fact that nonwage benefits are a relevant margin of adjustment for firms, especially in more regulated labor markets. They ease constraints and allow employers to partially absorb shocks, lowering the impact on employment.

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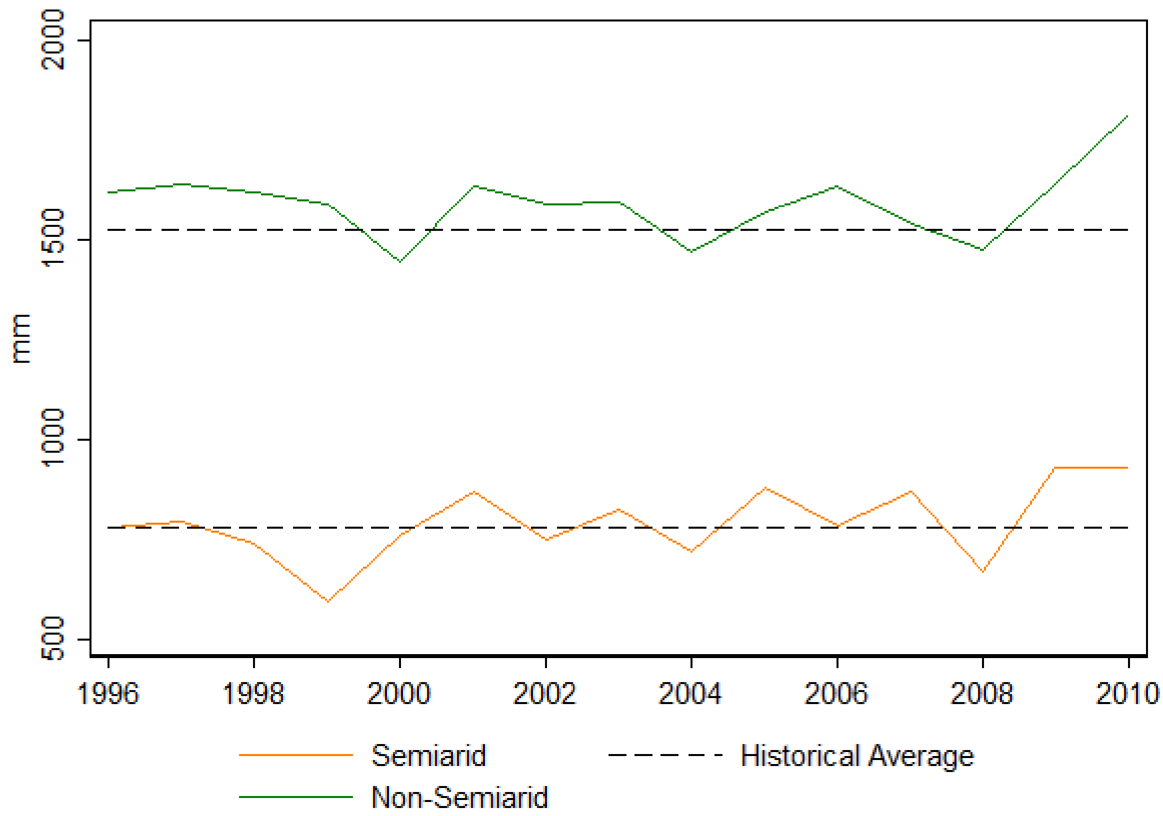
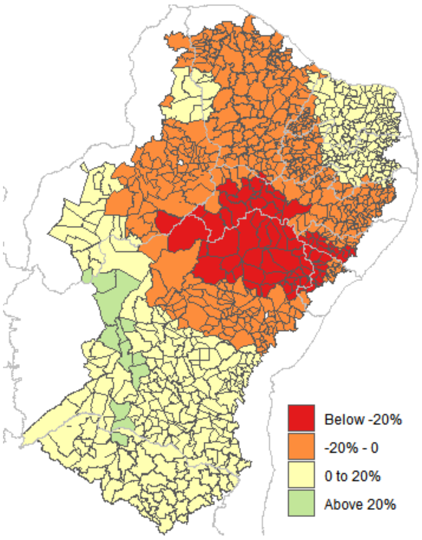
Figures and tables

Figure 11: **Precipitation level: Semiarid vs Non-Semiarid**

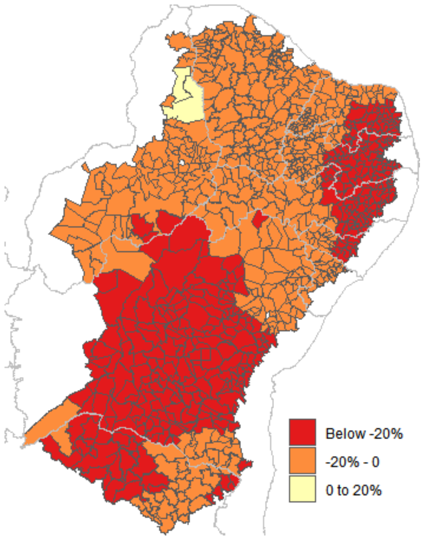


Notes: This figure compares the average precipitation level for the Semiarid region and the rest of the country, from 1996 to 2010. *Data source*: CRU Time Series v4 (Harris et al., 2020).

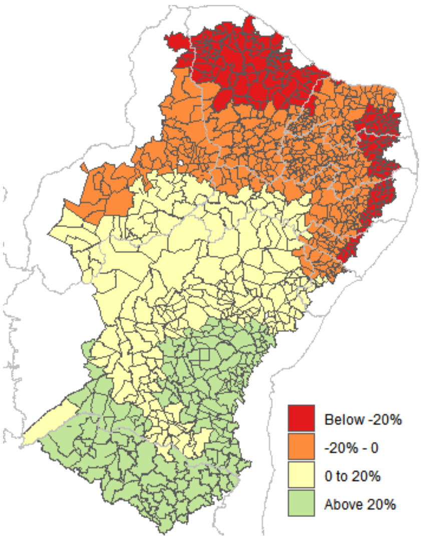
Figure 12: Precipitation levels in the Semiarid region for selected years



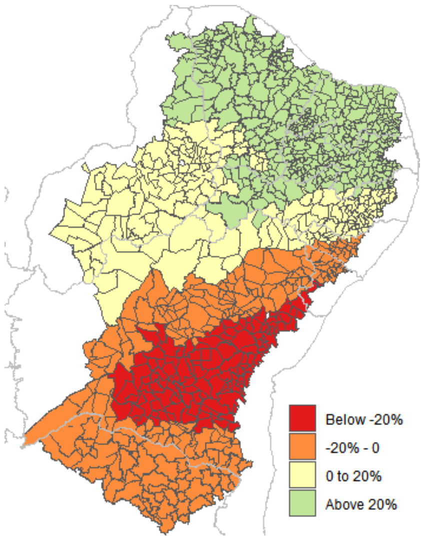
(a) 1997



(b) 2001



(c) 2005



(d) 2009

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

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

Panel A: Origin (Semiarid)	Mean	Std. Dev.	Min	Max	Obs
Annual Rainfall	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
	Non-wage benefits				
Food	38.89	21.06	0	100	8,165
Transport	36.39	25.40	0	100	8,165
Health	20.86	16.41	0	100	8,165

Notes: Each observation is a destination municipality-year cell. Earnings are measured in R$ of 2012. Informal sector also includes self-employed workers. Non-wage benefits are calculated only for native workers employed in the formal sector.

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

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

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

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

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall$_{t-1}$	-0.099***	-0.092***	-0.093***	-0.092***	-0.093***	-0.096***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.030)
Rainfall$_{t-2}$			0.008	0.022		
			(0.030)	(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 $\times$ time		✓	✓	✓	✓	✓

Notes: Each observation is an origin 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 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%.

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

	(1)	(2)	(3)
	A. Δ log earnings		
Migrant inflow	-1.323***	-1.252***	-0.869***
	(0.143)	(0.142)	(0.197)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
	B. Δ log earnings, formal sector		
Migrant inflow	-1.005***	-0.929***	-0.593***
	(0.171)	(0.169)	(0.198)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
	C. Δ log earnings, informal sector		
Migrant inflow	-0.986***	-0.908***	-0.746***
	(0.072)	(0.072)	(0.123)
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 log earnings, by sector. Each observation is an origin 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. Δ employment rate		
Migrant inflow	-0.011	-0.019	-0.018
	(0.022)	(0.022)	(0.034)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
	B. Δ formal employment rate		
Migrant inflow	-0.312***	-0.317***	-0.126***
	(0.025)	(0.025)	(0.037)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
	C. Δ informal employment rate		
Migrant inflow	0.301***	0.298***	0.108***
	(0.029)	(0.029)	(0.034)
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 employment rate, by sector. Each observation is an origin 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 unemployment and participation**

	(1)	(2)	(3)
	A. Δ unemployment rate		
Migrant inflow	0.167***	0.176***	0.094***
	(0.013)	(0.013)	(0.020)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
	B. Δ inactivity rate		
Migrant inflow	-0.155***	-0.157***	-0.077***
	(0.022)	(0.022)	(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 an origin 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 labor market outcomes, by status in the household**

	(1) Employment	(2) Formal	(3) Informal	(4) Unemployment	(5) 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 $\times$ time	✓	✓	✓	✓	✓

Notes: This table shows origin-level SSIV coefficients on changes in employment (by sector), unemployment and inactivity rates. Each observation is an origin 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 9: **Effects of migration on non-wage benefits**

	(1)	(2)	(3)
		A. Food	
Migrant inflow	-0.336***	-0.369***	-0.687***
	(0.062)	(0.063)	(0.086)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
		B. Transport	
Migrant inflow	-0.523***	-0.570***	-0.372***
	(0.040)	(0.040)	(0.062)
Observations	11,460	11,460	11,460
Municipalities	955	955	955
		C. Health	
Migrant inflow	-0.442***	-0.472***	-0.315***
	(0.043)	(0.044)	(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 an origin 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 10: Effects of predicted in-migration on employer-provider health insurance

	(1)	(2)	(3)	(4)	(5)
Predicted inflow	-0.015**	0.003	-0.004	-0.010**	-0.048**
	(0.007)	(0.002)	(0.003)	(0.005)	(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: This table shows the reduced form coefficients of changes in the probability of a firm offering health insurance to its employees on the predicted inflow of migrants from the Semiarid region. Each observation is a firm-year cell. 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 11: **Correlation between predicted migration from the Semiarid and other regions**

	(1)	(2)
	Migrant inflow from other regions	
Predicted inflow	0.080	0.081
	(2.847)	(2.848)
Observations	8,190	8,190
Municipalities	684	684
Municipality dummies	✓	✓
Time dummies	✓	✓
Baseline × 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. Each observation is a destination municipality-year cell. 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 12: **Effects of migration on earnings, by industry**

	(1)	(2)	(3)
	Agriculture	Manufacturing	Services
Predicted inflow	-0.466	-0.255	-0.831***
	(0.375)	(0.188)	(0.187)
Observations	11,447	11,460	11,460
Municipalities	955	955	955
1991 Demographics × Time	✓	✓	✓
Time dummies	✓	✓	✓

Notes: This table shows origin-level SSIV coefficients on changes in log earnings, by industry. Each observation is an origin municipality-year cell. All regressions 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. 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 effects**

	(1)	(2)	(3)
	Overall	Formal	Informal
	A. Δ log earnings		
Migrant inflow	-1.111***	-0.658***	-1.570***
	(0.312)	(0.253)	(0.265)
Observations	1910	1910	1910
Municipalities	955	955	955
	B. Δ employment rate		
Migrant inflow	-0.305***	-0.257***	-0.048
	(0.051)	(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. Each observation in an origin municipality-year cell. 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: **Long run impacts: non-wage benefits**

	(1)	(2)	(3)
	Food	Transport	Health
Migrant inflow	-0.112	-0.753***	-0.384***
	(0.124)	(0.088)	(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 non-wage 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 15: **Effects on migration outflows of natives**

	(1)	(2)	(3)	(4)
	Panel A. Low education			
Predicted inflow	1.352	1.273		
	(0.822)	(0.775)		
Lagged pred. inflow			-0.586	-0.342
			(0.615)	(0.450)
Observations	8,190	8,190	8,190	8,190
Municipalities	684	684	684	684
	Panel B. High education			
Predicted inflow	0.151	0.109		
	(0.746)	(0.750)		
Lagged pred. inflow			0.871	0.466
			(1.186)	(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. Each observation is a destination municipality-year cell. 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 Non-wage 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 non-wage 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 non-wage 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:

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

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.

$$W_i = \frac{\partial f}{\partial L_i^d} \tag{A2}$$

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

which yield labor demand equations assuming that the minimum wage is binding while non-wage 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 non-wage 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.[32]

In our model we consider that migration exogenously shifts the supply of workers to the informal and formal sectors. Suppose an equal increase of 10p.p. in the parameters g and j (intercept shifters), so that the total labor force M increases by 20p.p.

Table A1 shows the effects of migration on equilibrium allocations for each economy under two different scenarios: (i) with flexible non-wage benefits, and (ii) with non-wage benefits fixed at the baseline level. Panel A considers our benchmark economy with $c = f = 0.5$ while Panels B and C allow for higher and lower linkages in production across sectors, which is done by imposing $c = f = 0.7$ and $c = f = 0.3$, respectively. All baseline economies in column (1) are normalized to 100.

In columns (2) and (3) we show the effects of introducing migration in each scenario. Panel B shows that in the benchmark economy with medium production linkages across sectors and varying benefits (column (2)), migration increases unemployment and informal employment, and drops non-wage benefits and informal sector wages. Formal employment is unchanged. With benefits fixed at the baseline level (column (3)), the overall impacts on employment and informal wages are relatively higher since benefits do not adjust. Moreover, the formal employment declines.

Panel C considers an economy with higher linkages, the new equilibrium reflects a better adjustment of informal wages and non-wage benefits to the fact that there are wage rigidities in the formal sector, despite a lower value of non-wage benefits. Consequently the effects of migration with flexible non-wage benefits are lower than in the economy in Panel B. With fixed benefits, the impacts are even lower or nonexistent for most outcomes given the fast degree of market integration.

[32]We set our benchmark at $a = d = 1$, $g = j = 0$, $b = e = h = k = 1$ 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 non-wage 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 $M = 1$.

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

	(1) benchmark	(2) migration with B^*	(3) migration with $\overline{B}$
	Panel A: Low linkages		
L_f^*	100	100	88
L_i^*	100	115	124
W_i	100	93	89
B	100	33	100
U	100	128	156
	Panel B: Medium linkages		
L_f^*	100	100	89
L_i^*	100	109	119
W_i	100	94	90
B	100	45	100
U	100	183	283
	Panel C: High linkages		
L_f^*	100	100	100
L_i^*	100	103	100
W_i	100	96	100
B	100	96	100
U	100	98	97

Under lower linkages, Panel A shows that the qualitative results of Panel B are kept. However, migration induces a larger fall in informal sector wages and formal sector benefits with flexible formal sector benefits. With fixed benefits, the results in column (3) 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 more under fixed benefits in such 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.

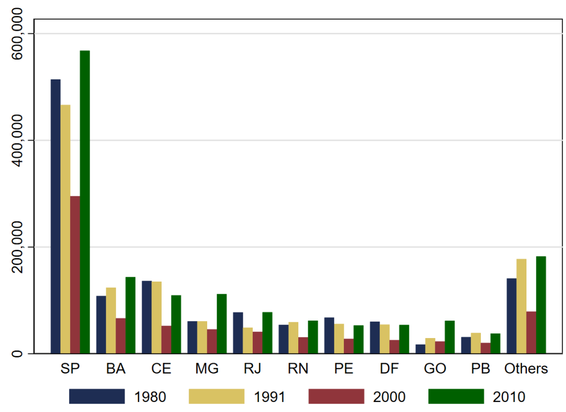
First, in the 2010 Census respondents were asked for how many years they had lived in the current municipality (from one up to ten). With this variable we are able to calculate the year when the individual have migrated. We consider migrant an individual who moved to the current municipality in the previous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

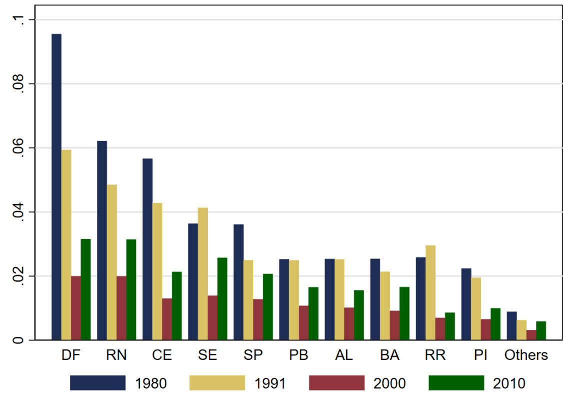
The Semiarid region has always been an important source of migrants for the rest of the country. Figure B1 shows that these migrants tend to be historically concentrated in some states. São Paulo alone harbored over 30 percent of the people arriving from the Semiarid in the last four decades. However, 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 less-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 B1 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 B2).

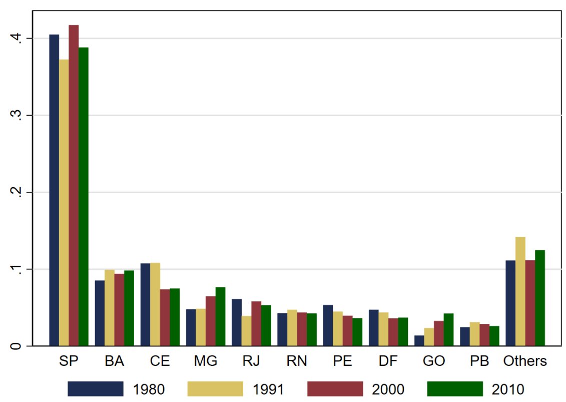
Figure B1: Top destinations for migrants from the Semiarid region



(a) Absolute number of Semiarid's migrants



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



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

Notes: This figure presents the main destination states chosen by migrants from the Semiarid region. Panel (a) shows the absolute number of migrants leaving the Semiarid region to non-Semiarid areas. 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 B1: **Main occupations for employed people: Migrants vs Natives**

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

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

Table B2: **Main industries for employed people: Migrants vs Natives**

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

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

Appendix 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 Antartica) from 1901 to 2018. The grid resolutions is $0.5° \times 0.5°$ (around 56km^2) and is created by interpolation from ground-based weather stations around the world.

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

This procedure results in a dataset of monthly averages of precipitation and temperature for each municipality in the Semiarid, from 1901 to 2010, 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 the natural logarithm of these variables (both levels and long term averages).

Finally, our weather shock variables are defined as

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

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

Table C1: **Migration outflows induced by weather shocks (12 months)**

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall$_{t-1}$	-0.126***	-0.107***	-0.111***	-0.117***	-0.112***	-0.109***
	(0.033)	(0.033)	(0.034)	(0.034)	(0.033)	(0.033)
Rainfall$_{t}$			-0.015	-0.029	-0.014	
			(0.039)	(0.041)	(0.039)	
Rainfall$_{t-2}$			0.037	0.059		
			(0.038)	(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%.

groundwater or any other factors that influence water balance. To circumvent this issue 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 2010, based on ground data from weather stations interpolated to create high-resolution grids ($0.25° \times 0.25°$) across the Brazilian territory. They calculate potential evaporation using maximum and minimum temperatures, solar radiation, relative humidity and wind speed. We aggregate the daily precipitation and evaporation data into monthly measures and follow Cavalcanti (2018) to construct a measure of drought severity, the aridity index, as follows:

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

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 de aridity index z-score as

$$Z^{AI}_{mt} = \frac{\left(AI_{mt} - \overline{AI}\right)}{AI_{sd}} \tag{C3}$$

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***	0.004***	0.004***	0.004***	0.004***	0.004***	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
Aridity Index$_{t-1}$		0.003***	0.003***	0.003***			
		(0.001)	(0.001)	(0.001)			
Aridity Index$_{t-2}$			0.001	0.001			
			(0.001)	(0.001)			
Aridity Index$_{t-3}$				0.000			
				(0.001)			
Aridity Index$_{t+1}$					0.001		
					(0.001)		
	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 grid 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

$$y_d^{\perp} = \beta m_d^{\perp} + \varepsilon_d^{\perp} \tag{D1}$$

where all $y_d^{\perp}$ is the vector of outcomes, $m_d^{\perp}$[33] is the observed number of Semiarid's migrants who entered the destination municipality d and $\varepsilon_d^{\perp}$ is an structural residual. All variables are residualized to remove the effects from the covariates.

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

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

where 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.[34]

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

$$\hat{\beta} = \frac{\sum_d \widehat{m}_d y_d^{\perp}}{\sum_d \widehat{m}_d m_d^{\perp}} \tag{D3}$$

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

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

where $\bar{y}_o = \dfrac{\sum_d s_{od} \frac{y_d^{\perp}}{P_d}}{\sum_d s_{od}}$ 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:

$$\bar{y}_o = \beta \bar{m}_o + \bar{\varepsilon}_o \tag{D5}$$

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

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

where $\tilde{o} = (o, t)$, $\bar{e} = \{\bar{e}_{\tilde{o}}\}_{\tilde{o}}$, $s_o = \sum_d s_{od}$ and $s = \{s_o\}_o$.[35] 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 D1 we present the effective sample size, which is calculated as the inverse of the Herfindahl concentration of migrants, $H = \dfrac{1}{\sum_o s_o^2}$. 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.

[35] As in Borusyak et al. (2021), $\bar{e}_{ot} = \frac{\sum_d P_d s_{od} \epsilon_{dt}}{\sum_d P_d s_{od}}$ correspond to the error term from equation 1 computed at the level of shocks (e.g. municipality of origin).

Table D1: **SSIV First Stage**

	(1)	(2)	(3)
First stage coefficient	0.912***	0.910***	0.925***
	(0.015)	(0.015)	(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 $\times$ 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 an origin municipality-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 working-age native population in 1991. 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 Semiarid 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.[36] Brazil has 5,565 municipalities, 361 micro and 87 mesoregions overall. The Semiarid has 960 municipalities, 137 micro and 35 mesoregions.

The intuition behind this exercise is that even if weather shocks are spatially correlated among contiguous municipalities, such correlation should decrease as we consider larger areas. Table E2 display Moran's index of spatial correlation of rainfall shocks for each of the three geographic aggregates in columns 1-3.[37] As expected, neighboring municipalities display correlation above 0,94, but it decreases rapidly as we aggregate up to micro and meso regions, to 0,16 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 5,6 and 9 using instruments corresponding to micro and mesoregion-level aggregation. Tables E3-E5 show that our results associating migration and earnings, employment and non-wage 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.

[36]Table E1 reports summary statistics of our main variables for all both levels of aggregation.

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

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

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 km^2.

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

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

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

Table E3: **Effects of migration on earnings according to different aggregation levels**

	(1)	(2)	(3)
	A. Δ log earnings		
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.869***	-0.846***	-0.871
	(0.197)	(0.302)	(0.550)
Observations	11,460	1,644	420
Regions	955	137	35
	B. Δ log earnings, formal sector		
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.593***	-0.558*	-0.556
	(0.198)	(0.290)	(0.527)
Observations	11,460	1,644	420
Regions	955	137	35
	C. Δ log earnings, informal sector		
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.746***	-0.745***	-0.769**
	(0.123)	(0.201)	(0.343)
Observations	11,460	1,644	420
Regions	955	137	35
Demographics	✓	✓	✓
Time dummies	✓	✓	✓

Notes: This table shows origin-level SSIV coefficients on changes in log earnings, by sector. Each observation is an origin 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 native working-age population in 1991. 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. Δ employment rate		
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.018	-0.003	0.007
	(0.034)	(0.058)	(0.091)
Observations	11,460	1,644	420
Regions	955	137	35
	B. Δ formal employment rate		
	Municipality	Micro-region	Meso-region
Predicted inflow	-0.126***	-0.117**	-0.125
	(0.037)	(0.055)	(0.098)
Observations	11,460	1,644	420
Regions	955	137	35
	C. Δ informal employment rate		
	Municipality	Micro-region	Meso-region
Predicted inflow	0.108***	0.114**	0.133
	(0.034)	(0.057)	(0.095)
Observations	11,460	1,644	420
Regions	955	137	35
Demographics	✓	✓	✓
Time dummies	✓	✓	✓

Notes: This table shows origin level SSIV coefficients of Δ the proportions of employed natives, by sector. Each observation is an origin 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 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. All regressions are weighted by native working-age population in 1991. Standard errors clustered at the municipality level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.

Table E5: **Effects of migration on non-wage benefits according to different aggregation levels**

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

Notes: This table shows origin level SSIV coefficients of change in the proportions of formal sector workers who receive health insurance, food or transport subsidies. Each observation is an origin municipality-year cell. 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 9. In columns (2) and (3) we aggregate the origin-level shocks at the micro- and meso-region levels, respectively. All regressions are weighted by native working-age population in 1991. Standard errors clustered at the municipality level in parentheses. *** Significant at 1%. ** Significant at 5%. * Significant at 10%.