Long-term effects of weather-induced migration on urban labor and housing markets*

Matias Busso and Juan Pablo Chauvin

Research Department
Inter-American Development Bank

September, 2024

Abstract

This paper explores the effects of weather-induced rural-urban migration on labor and housing market outcomes of urban residents in Brazil. In order to identify causal effects, it uses weather shocks to the rural municipalities of origin of migrants. We show that larger migration shocks led to an increase in employment growth and a reduction in wage growth of 4 and 5 percent, respectively. The increased migration flows also affected the housing market in destination cities. On average, it led to 4 percent faster growth of the housing stock, accompanied by 6 percent faster growth in housing rents. These effects vary sharply by housing quality. We find a substantial positive effect on the growth rates of the most penurious housing units (with no effect on rents) and a negative effect on the growth of housing units in the next quality tier (with a positive effect on rents). This suggests that rural immigration growth slowed down housing-quality upgrading in destination cities.

JEL classifications: J46, J61, O18, R23

---

*Corresponding authors: Busso (mbusso@iadb.org) and Chauvin (juancha@iadb.org). We thank Guillermo Alves, Sandra Aguilar Gomez, A. Patrick Behrer, Shekhar Tomar, and seminar participants at the 12th European Meeting and the 17th North American Meeting of the Urban Economics Association, XVII RIDGE Forum's Workshop on Poverty and Inequality, the 2nd Annual LAUrban Meeting, and the 28th Annual LACEA meeting for their helpful comments and suggestions. We are also grateful to Antonella Rivera, Nicolás Herrera L., Rafael Macedo R., Anna F. Matos, Julio Trecenti, and Haydée Swab for their outstanding research assistance.

1. Introduction

Climate change is expected to increase the frequency and intensity of extreme weather events. Such events are frequently associated with the displacement of rural populations, particularly in developing countries. Distressed lives in rural communities lead workers to pursue better opportunities elsewhere, and a large share of those migration flows are directed to cities. Much of the literature studying the economic effects of weather shocks has emphasized the impact on local labor markets, primarily in affected rural areas (for example, Kleemans and Magruder 2018; Corbi et al. 2023). In this paper we study the long-run effects of weather-induced rural migration to cities on both urban labor markets and urban housing markets in Brazil.

We look at both labor and housing because outcomes in these markets are closely intertwined. Increases in labor supply following migration shocks are likely to increase the local demand for housing, pushing prices up and slowing further migration (Glaeser, 2008). Higher housing demand can also lead to increased local labor demand, not only through growth in the construction sector but also because raising housing prices can lead to substantial increases in the demand for local goods and services by homeowners (Berger et al., 2018; Stroebel and Vavra, 2019). These effects are in turn mediated by the local elasticity of housing supply. Housing supply in developing countries can be more heterogeneous and segmented than in high-income countries, and it includes penurious housing with barely any access to public services (like sewage or running water), low-quality social housing located far from job centers, and more conventional housing. The type of housing that migrants demand and the relative supply of that type of housing shape the ultimate effects on housing prices and labor demand.

To identify the causal effects of weather-induced migration to cities, we follow a recent literature (for example, Kleemans and Magruder 2018; Albert et al. 2024; Ibañez et al. 2022) in constructing a city-level instrument using weather variation in rural municipalities of origin interacted with the shares of each rural municipality of origin in the historical rural–urban migration to the city. Specifically, the weather variation captures fluctuations in dryness based on the reverse average monthly Standardised Precipitation Evapotranspiration Index of Vicente-Serrano et al. (2010). We adopt the quasi-experimental econometric framework for shift-share instrumental variables developed by Borusyak et al. (2022), in which identification relies on the exogeneity of the shocks component of the instrument – in our case, the weather fluctuations in the rural municipalities of origin of migrants. We also use this framework's approach to conduct valid inference, which addresses the fact that cities with similar exposure shares are likely to have correlated residuals, rendering conventional standard errors invalid. After providing validation tests for this research design, we show that our measure of dryness predicts emigration rates in rural municipalities and that our instrument is a good predictor of rural-urban migration inflows to the cities in our sample.

Our results show that weather-induced migration affects both the urban labor and housing markets in the long run. In the labor market, the influx of rural migrants reduced urban residents' wage growth by 5 percent and increased their employment growth among urban residents by 3.8 percent, consistent with a downward-sloping long-run demand schedule. The effects on wages are relatively stronger in the services sector (-7.5 percent), while the impact on employment is relatively stronger in the manufacturing sector (15 percent). The effects on prices and quantities are larger for more educated workers. In light of standard economic models, we interpret this as evidence of long-term adjustments in the labor market. We find that residents in destination cities reduced their participation in industries where they likely faced competition from migrant workers and increased their schooling attainment, shifting the labor supply of the more skilled workers outwards.

Our housing market results show that rural-migrant inflows led to faster growth in quantities of resident-occupied housing. The number of units increased by 3.6 percent, and the number of rooms available by 4.5 percent. The inflow of migrants also led to a 6.1 percent faster growth in average housing rents, consistent with an upward-sloping long-run housing supply curve. These results, however, mask meaningful heterogeneity. While in the lowest tier of housing quality ("penurious" housing), rural-immigrant inflows have a positive effect on quantities and no significant effect on rents, in the next quality tier, they have a positive effect on rents and a negative effect on quantities (the magnitudes of the impact on quantities are even larger for the highest quality tier but results are marginally not statistically significant). These results suggest that rural-urban migrants are more likely to demand the most basic type of housing, which is also the most affordable, than higher-quality types. In a period in which overall housing quality increased across the country, inflows of weather-displaced rural-urban migrants slowed down these improvements. In addition, we show that the relatively lower availability and affordability of higher-tier housing appear to have reduced homeownership rates in cities with higher migration rates.

Our results are robust to alternative specifications. The estimates do not seem to be biased by migration-driven agglomeration effects. We also show that our results hold with a different measure of the weather shock and when accounting for more cyclical precipitation patterns coming from El Niño Southern Oscillation (ENSO). Finally, because our main outcomes are city-level averages computed from individual data, price differences between cities may reflect compositional variations. We address this concern in two ways. In all our specifications, we rely on wage and rent measures that have been residualized – using observable characteristics. To account for the possibility of sorting, we follow Combes et al. (2008) two-stage procedure and find similar results to our main specifications – in terms of the magnitude of the point estimates and their statistical significance.

Our work contributes to the broader literature on the effects of weather fluctuations on the economy. This large and growing literature has provided credible causal evidence that changes in weather influence multiple economic outcomes (Dell et al., 2014). The documented effects are frequently negative; for example, higher temperatures have led to lower agricultural output and lower economic growth, particularly in poor countries (Dell et al., 2012). A strand of this literature has emphasized the effects of weather changes and extreme weather events on migration, documenting that such events increase emigration out of affected areas, particularly in developing countries (Cattaneo and Peri, 2016; Oliveira and Pereda, 2020). Our paper expands this literature by studying how these weather-driven migrations, in turn, affect the economy of destination urban areas.

Our paper also contributes to an extensive literature that studies the effects of immigrants—mostly international—on local labor markets. Dustmann et al. (2017), for example, study the effects of shocks to local labor supply induced by an unexpected commuting policy that led to a large inflow of Czech workers along the German-Czech border; they find moderate impacts on wages but large impacts on employment among natives. Calderón-Mejía and Ibáñez (2016) consider internal migration, studying the effects on urban labor markets of inflows of refugees escaping rural armed violence in Colombia, and find that migrant inflows substantially reduce wages among urban unskilled workers. Our study contributes to this literature by studying how weather-induced internal displacement affects not only local labor markets but also local housing markets.

Our work is most closely related to three recent papers that use weather variation to predict migration in the Brazilian context. Albert et al. (2024) study the economic impact of extreme weather events on the economies of the affected areas and the reallocation of labor and capital across the national territory, including both urban and rural areas. Corbi et al. (2023) study the effects of weather-induced migrants from the semi-arid region in Brazil on local labor markets in both rural and urban receiving communities. More recently, Imbert and Ulyssea (2024) studied the labor market effects of rural migration in Brazilian cities, focusing on how it affects labor informality. Our study focuses exclusively on urban areas and finds effects on urban labor markets that are broadly consistent with these three studies, validating our approach. Our key contribution consists of incorporating local housing markets into the literature on the effects of weather-induced migration. This is important because housing markets can shape how local labor markets respond to migration shocks and can deter subsequent migration flows by making city living more expensive. Furthermore, it highlights that housing policy can become an important part of policymakers' toolkit to tackle future–potentially growing–inflows of weather-induced migrants.

Lastly, our paper contributes to a recent literature studying the link between urban housing supply and migration. Rozo and Sviatschi (2021) estimate reduce-form effects of the influx of Syrian refugees to Jordan since 2011, and find that it leads to higher housing expenditures among Jordanians only in locations where the housing supply is unresponsive. Alves (2021) calibrates a structural spatial equilibrium model in Brazil, and finds that the effects of housing demand shocks on rents are significantly larger among non-slum households than among slum households, suggesting that housing supply is more elastic in slums. Guedes et al. (2023) study how housing supply elasticity varies across Brazilian cities with different levels of housing informality, finding larger elasticities in cities with more informal housing. Our paper does not focus on the study of housing supply elasticities per se but on understanding how heterogeneity in the housing market shapes the effects of rural-urban migration. An implication emerging from this literature is that the housing market effects of immigration can be highly heterogeneous, reflecting segmentation and potentially large differences in housing supply elasticity across different segments. Our paper expands this literature by explicitly exploring this implication, and showing that, following rural immigration shocks, quantity effects are substantively larger in segments where the literature suggests there is a higher elasticity, and price effects are larger in segments where we expect more inelastic housing supply.

The rest of the paper proceeds as follows. Section 2 outlines the plausible mechanisms that may operate in labor and housing markets, both in the short- and in the long-run, in response to a migration shock. Section 3 describes our data sources, the computation of our weather shocks, the empirical specification we use in the analysis, and assesses the validity of our research design. Section 4 presents the basic descriptive statistics, and discusses the main results – including heterogeneous effects and robustness tests. Section 5 investigates other effects of migration on local economies that help us interpret our main results. Section 6 concludes.

2. Migration Externalities in Local Economies

The literature on migration, labor, and urban economics provides a conceptual framework that informs the interpretation of our estimates of the effects of migration on the labor and housing markets, sheds light on the mechanisms that can drive those results, and suggests potential issues for identifying the causal effects of migration on the outcomes of interest.

2.1. Migration and the Local Labor Market Outcomes of Residents

To characterize the forces that can shape the effects of migration on the labor market outcomes of residents, it is helpful to distinguish between short-run partial effects—those that occur before any market adjustments, such as changes in the location or industry choices of residents—and long-run total effects, which incorporate those market adjustments (Lewis and Peri, 2015).

The partial effects depend on whether migrants' labor is a net substitute or a net complement in production to residents' labor (Ottaviano and Peri, 2012). If migrant labor is a net substitute, migrant inflows amount, from the residents' perspective, to a positive labor supply shock and a negative impact on residents' wages. Residents' employment, in turn, is expected to increase if the labor demand curve is downward-sloping—since quantities of labor demanded would be larger at higher wages—or remain unchanged if it is perfectly inelastic. Conversely, if migrant labor complements residents' labor, the inflow of migrants should increase demand for residents' labor, with a positive effect on wages and effects on employment that are positive if residents' labor supply is upward-sloping, or null if supply is fully inelastic.

The substitutability of migrant and resident labor, in turn, depends on the skill similarity between the two groups. The literature frequently distinguishes between high- and low-skilled workers and assumes that workers of the same skill are net substitutes, while workers of different skills are net complements (Peri, 2016). Rural-urban migrants tend to have relatively lower schooling attainment than residents and are thus traditionally treated as part of the low-skilled group (e.g., Combes et al. 2015; Corbi et al. 2023). In this context, theory predicts that the partial effect of rural-urban migration on wages will be negative for low-skilled residents and positive for high-skilled residents.

Our empirical analysis explores reduced-form effects on residents' outcomes in the long run. Over this period, residents may adjust their labor supply choices in response to the short-run, partial effects of migration, which can have a feedback effect on their labor market outcomes (Lewis and Peri, 2015). Residents could move away from jobs in which they are substitutes for migrant labor towards jobs in which they are more complementary (Peri, 2016). For example, they may change their labor force participation choices (Dustmann et al., 2017), their industry or occupation (Llull, 2018), or even move to a different labor market, affecting local labor supply (Boustan et al., 2010). Residents could upgrade their skills over time, becoming more complementary to migrants (Hunt, 2017; Llull, 2018). Moreover, the expansion of the local labor force may create incentives for firm entry, increasing labor demand for both residents and migrants (Imbert and Ulyssea, 2024). In Section 5, we explore these mechanisms' role in shaping the total effects of migration on the labor market outcomes of residents.

Two additional features of local labor markets are important to consider in our context. The first is the connection between agglomeration and productivity. Numerous studies have shown that the density of economic activity increases productivity.[1] Because the arrival of migrants expands the size of the local workforce, it can positively impact residents' wages through these agglomeration effects. Combes et al. (2015) argue that this effect may be a source of bias: without controlling for the effects of migration on employment density, estimates of the substitution/complementarity effects of migration on residents' labor market outcomes may partially capture agglomeration effects. In our empirical section, we explicitly address this concern.

Second, in Brazil, as in many other developing economies, the informal sector represents a large share of local employment. The formal and informal sectors tend to be integrated into the same markets, co-existing within industry and occupation categories, even when narrowly defined (Ulyssea, 2018). Moreover, there is extensive evidence of significant overlap

[1] See Combes and Gobillon (2015) for a comprehensive overview of this literature.

between the formal and informal firms' distributions of size and productivity (Busso et al., 2012; Meghir et al., 2015; Perry et al., 2007; Ulyssea, 2018). In line with this literature, we treat formal and informal jobs as part of a single local labor market. Regarding urban migrants, because informal labor demand tends to be more elastic than formal labor demand,[2] migration shocks are likely to increase informal more than formal employment, thus raising local informality rates in the short run. As with other outcomes, long-run effects can be different, as migration-led wage reductions can stimulate formal firms entry, increasing formal labor demand and decreasing informality rates (Imbert and Ulyssea, 2024).

2.2. Migration and Local Housing Markets

The arrival of migrants represents a demand shock to local housing markets. Its impact on prices and quantities will depend on the elasticity of supply. We assume that local housing markets are segmented on housing quality. The bottom segment ("penurious housing") is composed of stereotypical "slum" houses, built with low-quality materials on land that lacks municipal services or has other undesirable characteristics (e.g., property rights that are not legally recognized, steeply sloped terrain, high risk of landslides, etc.). Because development is not constrained by the availability of municipal services and regulations, housing supply in this segment is highly elastic. Recent evidence from Brazil supports this assumption: Alves (2021) estimates that the rent response to housing demand shocks in Brazil is more than five times larger in non-slum households than in slum households, and Guedes et al. (2023) find that housing supply elasticity is larger in Brazilian cities with a greater presence of informal housing.

The middle segment ("low-quality housing") includes mostly formal units that lack either good materials or access to municipal services. While this type of housing has previously been classified together with penurious housing in a generic slums category (e.g., Alves 2021), we find it useful to distinguish these two segments, as the supply of low-quality housing is, in principle, less elastic due to restrictions from zoning and other building regulations, as well as higher construction costs.

[2] Informal workers' wages have less downward rigidity than those of formal workers, as they do not abide by minimum wage and other regulations. Informal workers also lack access to other benefits such as social security and job tenure protections. From the employer's perspective, the lack of regulation implies lower hiring costs, making informal labor demand more elastic. Regulation enforcement and related sanctions can, in turn, increase costs, discouraging informal hiring and reducing differences in the formal and informal labor demand elasticities.

The top segment ("quality housing") consists of formal housing built with high-standard materials and with access to all municipal services. In addition to regulation and building costs, supply in this segment is constrained by the availability of land with municipal services, resulting in lower elasticity.

While migrants and residents participate in all segments of the housing market, rural-urban migrants—particularly those displaced from their villages due to weather or other shocks—are likely to face more constraints than residents in accessing higher segments of the market. They may lack access to credit, savings to pay security deposits, connections willing to act as co-signers in formal rental contracts, or knowledge about housing quality and availability in different neighborhoods (Busso et al., 2023). As a result, their arrival in the city is likely to have a larger impact on housing demand in the lower segments of the market.

As in the case of the labor market, the total effects of migration on local housing markets in the long run may differ from the short-run, partial effects. Beyond the expansion of available housing, the composition of local housing supply may also change. One possibility is that lower-quality units could be upgraded over time, as municipal services expand and incomes rise, along with private home investments. Conversely, as theorized by Brueckner and Selod (2009) and empirically validated by Brueckner et al. (2019) using Brazilian data, early housing development in lower-tier segments could "squeeze" future higher-tier supply as they compete for scarce urban land. Additionally, higher costs and institutional frictions could limit the conversion from lower to higher-quality housing (e.g., as in Henderson et al. 2021). These dynamics could reduce homeownership rates in the long run, particularly in less elastic market segments, as newly formed families may find it increasingly difficult to afford homeownership in these tiers.

3. Empirical Strategy

3.1. Geographies and Data

Our analysis focuses on urban areas. Following Busso et al. (2021), we use *arranjos populacionais* as our definition of "urban areas" in Brazil. These are units similar to US commuting zones, and they consist of urban cores and their surrounding municipalities tied to the cores through commuting links (IBGE, 2016).[3] Each urban area consists of at least one municipality. We consider all municipalities that are not part of one of these cities *rural municipalities*. Each rural area consists of one municipality.

Most of our variables, including migration, demographic, labor-market, and housing-market measures, are based on the microdata of the long-form questionnaire of four rounds of the decennial population census produced by the Brazilian Institute of Geography and Statistics. These are large random samples representative at the municipality level.[4] For 1980 they include 25 percent of the population, and for 1991, 2000, and 2010, they include 10 percent.

Making comparisons across time requires adjustments for changes in administrative boundaries. We follow the approach of Reis et al. (2007) in creating time-consistent municipalities based on the smallest comparable area for the 1980–2010 period[5], and then group them into time-consistent urban areas and time-consistent rural municipalities. We then use the microdata of the population censuses to compute area-level measures for these cities and rural areas.

In order to capture weather variation by rural locality, we rely on the average monthly Standardised Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010). This index measures climatic water balance by comparing the observed precipitation with the amount of water required to preserve surface moisture. The precipitation required to preserve moisture, in turn, depends on evapotranspiration, the water lost to the atmosphere through surface evaporation and transpiration. Evapotranspiration varies seasonally and, critically to our research design, varies regionally.[6] This measure depends on various atmospheric

[3]For simplicity, we use the term "urban areas" and "cities" interchangeably in this paper.

[4]Municipalities are typically small units, with average population of 34,500 and area of 1,500 square kilometers in 2010, although they also include a few very populated units, reaching upward of 6 million people in Rio and 11 million in São Paulo in that year. Over the period of study, the number of municipalities increased significantly, going from 3,952 in 1970 to 5,565 in 2010.

[5]The Reis et al. (2007) Minimum Comparable Area (MCA) definitions are readily available on the Institute of Applied Economic Research (IPEA)'s website (http://www.ipeadata.gov.br) and have been used in a number of studies of Brazilian local economies (for example, Dix-Carneiro and Kovak 2017; Kovak 2013). However, as noted in Chauvin (2018), the 3,659 IPEA MCAs corresponding to our period of interest are more aggregated than needed (for example, they include in the same MCA municipalities that used to be joined at the beginning of the twentieth century but had already been separated by 1970). Thus, we construct the MCAs' 1970–2010 boundaries directly, based on the algorithm from Chauvin (2018).

[6]The SPEI data that we use are provided in a grid with cells of spatial resolution of 0.5° latitude and longitude. To capture moisture variation within the boundaries of each rural MCA, we employ Wiener–Kolmogorov predictions ("kriging") to interpolate the original data using the cell centroids as the

factors, especially temperature. It is a better predictor of droughts than measures based only on precipitation data such as the Standardized Precipitation Index, and it has been used in prior studies of weather-induced migration (for example, Kubik and Maurel 2016; Albert et al. 2024). To simplify the discussion of our results, we follow Albert et al. (2024) and reverse the original SPEI measure (multiplying it by -1) so that we can interpret the index as a measure of dryness. Thus, a value of 1 indicates dryness that is one standard deviation higher than the historical average in a given locality, while a value of -1 indicates wetness that is one standard deviation higher.

We complement our main data with selected variables from other sources, including the geographic area of each municipality from the Brazilian Institute of Applied Economic Research and geographical data from the Brazilian Institute of Geography and Statistics. Appendix A provides further details on the sources and computation of the variables we use in the analysis.

3.2. Main Specification

To estimate the effects of the inflow of rural migrants on urban economies, we rely on a city-level regression of the following form:

$$\Delta Y_c = \alpha + \beta I_c + X_c' \mathbf{\Theta} + \varepsilon_c \quad (1)$$

Here, α is a constant, ΔY_c is the log difference in the outcome of interest Y (for example, log wages or log rents) in city c; I_c is the rural immigration rate to that city (expressed as a percentage of the baseline population); $X_c{}'$ is a vector of controls; and $\mathbf{\Theta}$ is a vector of parameters for the controls. ε_c is the city-level error term.

One limitation of our study is that, given the available data, we are only able to compute the endogenous variable I_c for a 10-year interval.[7] Accordingly, we define the dependent variable as the number of rural immigrants that migrated between 2001 and 2010 as a fraction of the 1991 city population. Meanwhile, because data for our full set of outcomes

origin locality and the MCA's centroid as the target locality.

[7]We only observe the municipality of origin for the second half of our period of analysis because the 2010 census microdata contains the year of migration and the municipality of prior residence—which we need in order to identify rural migrants—only for migrants who moved between 2001 and 2010.

are only available in 1991 and 2010,[8] we measure our dependent variables in equation 1 as long changes over these two decades. This raises the possibility that city outcomes may have shifted between 1991 and 2000—reflecting either the initial response of agents to migration in this period or other economic shocks—and changes relative to the year 2000 may differ from those relative to our baseline. This caveat notwithstanding, using 1991 as a reference year allows us to capture long-term, reduced-form effects, which we interpret as the result of both the partial effects of migration and the effects of subsequent market adjustments.[9] The available data does allow us to compute outcomes for the period 2000-2010 in the labor market. In Appendix B, we estimate the migration effects in this subset of outcomes using 2000 as the reference year and discuss the results and their connection to our main findings in light of the theory presented in Section 2.1.

Our primary outcomes of interest are prices and quantities in the local labor and housing markets. The key labor-market variables are local average wages and total local employment among residents. The wage measure is the log of the geometric mean of the wage adjusted for individual human-capital characteristics.[10] Specifically, we use the average of the estimated residuals of an individual-level regression of the logarithm of the monthly wages on a vector of schooling attainment indicators and a vector of age categories indicators. In order to explore the mechanisms of adjustment of local economies to the partial effects of migration—which, as discussed in Section 2.1, also contribute to the long-run effects—we also measure the impact of migration on the labor force participation of residents, their likelihood to move to a different local economy, the industry composition of resident's employment, resident's educational attainment, and informality rates.[11] All labor-market outcome variables are computed for working-age individuals (14 to 64 years old).

In the housing market, we focus on residents-occupied housing and consider two measures of quantity: the total number of housing units, which captures the extensive margin of housing growth, and the total number of rooms, which captures both the extensive and the intensive margins. We measure price variation using the logarithm of the geometric mean of

[8]Specifically, the data that we require to study the impact on the local housing markets—in particular, rents—were only collected in the 1991 and 2010 rounds of the census.

[9]This interpretation requires us to assume some persistence in our exogenous variation over the two decades of analysis. As described in Appendix B, we find support in the data for making this assumption.

[10]We use the geometric mean for monetary values (i.e. wages and rents) as it is less sensitive to extreme values than the arithmetic mean.

[11]For all outcomes measured in shares, we use the simple difference in the 2010 and 1991 shares rather than the log difference.

the rent. Specifically, we obtain the estimated residuals of a household-level regression of the logarithm of the monthly rent (for all households that report positive rents) on a vector of dwelling characteristics: number of rooms, access to sewage, and access to trash collection.[12]

The controls vector is chosen to account for local attributes that could influence migration patterns, and by extension, labor and housing market outcomes. These attributes could also correlate with weather variations. Indeed, Brazil is characterized by great disparities across its main regions. The five primary "macroregions" exhibit stark differences across multiple dimensions, including levels of development and climate. To account for these differences and to ensure a more homogeneous comparison, we incorporate macroregion fixed effects into all of our specifications. This allows us to examine the effects of weather within territories that are broadly similar. Even within macroregions, economically lagging areas (typically more agricultural and less educated) may be located in settings that are more prone to negative weather shocks. To address this concern, we control for the economic structure of the local economy (shares of manufacturing, services, and government in employment), schooling level (share of college-educated workers in employment), the log of 1991 population, and population growth in the prior decade (1980–91) to account for preexisting migration trends.

In addition, we perform subgroup analysis to explore heterogeneous effects. In the labor market, we explore heterogeneity by industry, schooling attainment, and the effects on the outcomes of recent migrants. In the housing market, we use a set of four housing attributes consistently defined across censuses—access to running water, sewage network, trash collection, and brick walls—to create housing-quality categories. As discussed in Section 2.2, we classify housing into three segments. A housing unit is classified as *penurious* if it is missing all four of these attributes, as *low quality* if it is missing at least one (but not all), and as *quality* if it is not missing any of these attributes. Prior studies have adopted a similar approach to studying slums. Alves (2021), for example, uses two of these attributes (access to water and to sewage) to define slum households in the Brazilian census, which is, in turn, an adaptation of the UN definition of slum households across the world (UN-Habitat, 2004).

A limitation of this approach is that housing rents are not always available in the microdata, either because renting households do not report the rent value, or because there are no renter households within a given housing quality category in a given city. This is more fre-

[12]We view the measures of access to these services as a proxy for neighborhood quality.

quent at the extremes of the housing quality distribution (i.e. penurious housing and quality housing). As a result, the number of observations varies across categories, specifically, there are 453, 166, 450, and 299 observations for all, penurious, low-quality, and quality housing categories, respectively. In each category, we exclude all observations that do not have housing rents data, even if they have data on the number of housing units and the number of rooms. This ensures that our estimates of the effects of immigration on housing on prices and quantities are based on the same samples.

3.3. Weather-Based Instrument for Migration

Immigration rates to cities are endogenous to the conditions of local economies. To identify the effect of migration on urban labor- and housing-market outcomes, we follow the tradition of a large migration studies literature (starting with Altonji and Card 1991 and Card 2001) by combining historical migration patterns with an exogenous migration push factor (namely, weather shocks) to construct an instrumental variable Z_c, calculated for city c for the 2000–2009 period,[13] which is defined as follows:

$$Z_c = \sum_r s_{c,r} D_r \tag{2}$$

Here, $s_{c,r}$ is the share of total rural immigrants that arrived in city c from rural area r between 1982 and 1991 and D_r is the average of the monthly reversed SPEI for all months between 2000 and 2009 (that is, the average dryness shock to rural location r). Other recent studies that also use "shift-share" instruments constructed from weather shocks and historical migration patterns in the context of Brazil include Albert et al. (2024), Corbi et al. (2023), and Imbert and Ulyssea (2024).

Validity of the Design

While shift-share instrumental variables have been used for decades in economics following early work by Bartik (1991) and Blanchard and Katz (1992), a recent literature has greatly expanded our understanding of the conditions under which they provide a valid identification

[13]We construct the instrument for the same period as the endogenous migration variable, but with a one-year lead to allow time for the migration response to occur. Computing the instrument using 2001-2010 weather shocks instead, makes no meaningful difference in the results.

strategy. Two alternative econometric frameworks have emerged, one that requires exogeneity of the "shares" component of the instrument (Goldsmith-Pinkham et al., 2020), and another that requires exogeneity of the "shocks" component, while allowing for endogenous shares (Borusyak et al., 2022). In our application, the "shocks" used in the IV (weather deviations from historical patterns) can be considered instruments themselves, making the second approach a more fitting choice.

Within this framework, identification in our application relies on two assumptions: that the weather shocks are (conditionally) quasi-random, and that there are many uncorrelated shocks—such that a shock-level law of large numbers is applicable. Moreover, under this approach, conventional standard errors may be incorrect, because unobserved confounders at the shock level (in our case, at the level of rural municipalities) can result in dependencies between the shift-share instrument (Z_c) and the main regression's error term (ε_c) if multiple observations have similar exposure shares.[14] Borusyak et al. (2022) propose a method to address this issue, generating "exposure-robust" standard errors. Unless otherwise noted, all regression results reported in this paper are constructed using this approach.[15]

To assess the validity of the shift-share research design in this context, we first assess the plausibility of the first identifying assumption (i.e., quasi-random assignment of shocks). Specifically, we regress the variables in our controls vector—which we expect to be correlated with the unobserved residual—on the SPEI-based shift-share IV, controlling for macroregion fixed effects. Table 1 presents the resulting point estimates and exposure-robust standard errors.

We find no statistically significant relationship between the employment shares—which capture the industry composition of the city—or the share of college-educated in employment with the shift-share instrument within macroregions. We find that cities exposed to larger shift-share shocks tend to have a smaller baseline population. This is not surprising given the context of our analysis: relative to large cities, smaller cities draw immigrants from a smaller pool of rural municipalities, and these are more likely to be located in economically lagging areas and prone to negative weather fluctuations.[16] Reassuringly, we find no significant

[14] Appendix C further discusses these identifying assumptions and inference challenges in the context of our application.

[15] The method requires transforming city-level to rural-area-level variables, which we implement using the *ssaggregate* Stata package provided by Borusyak et al. (2022).

[16] A recent literature has highlighted the role that distance and other migration costs have in the decision to migrate in Brazil (e.g. Oliveira and Pereda 2020; Morten and Oliveira 2023). In regions where potential

correlation between the shift-share IV and lagged population *growth*.[17] We control for the logarithm of 1991 population throughout our analysis (to assess the possibility of omitted variable bias, we report estimates with and without this control). The sensitivity of the coefficients to this control variable is minimal, and the significance of our results is typically unaffected.

Table 1: Balance in city-level covariates

	Coefficient	Exposure-robust standard error
	(1)	(2)
Panel A: Base-year variables (1991)		
Local industry structure		
Share of manufacturing in employment	-0.006	(0.004)
Share of services in employment	-0.008	(0.005)
Share of government in employment	0.000	(0.001)
Share of college-educated in employment	-0.000	(0.001)
Log of population	-0.083**	(0.037)
Panel B: Lagged changes (1980-1991)		
Lagged population growth	0.000	(0.007)
Lagged shift-share IV	-0.008	(0.007)

Notes: The table reports the results of regressions of city-level covariates and pre-trends on the shift-share instrument, controlling for macroregion fixed effects. Exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in equation 5 are reported in column 2. * p <0.1, ** p < 0.05, and *** p < 0.01.

In order to assess the assumption of a large-enough number of shocks, we follow Borusyak et al. (2022) who suggest using the inverse Herfindahl Index (HHI) of the shock-level exposure shares as a measure of the effective sample size. We find that, in our rural-municipality-level dataset constructed by recasting the original city-level variables, $HHI_r = 1/\sum_r s_r^2 = 1,283$. This suggests that the number of shocks is large enough for the law of large numbers to apply.

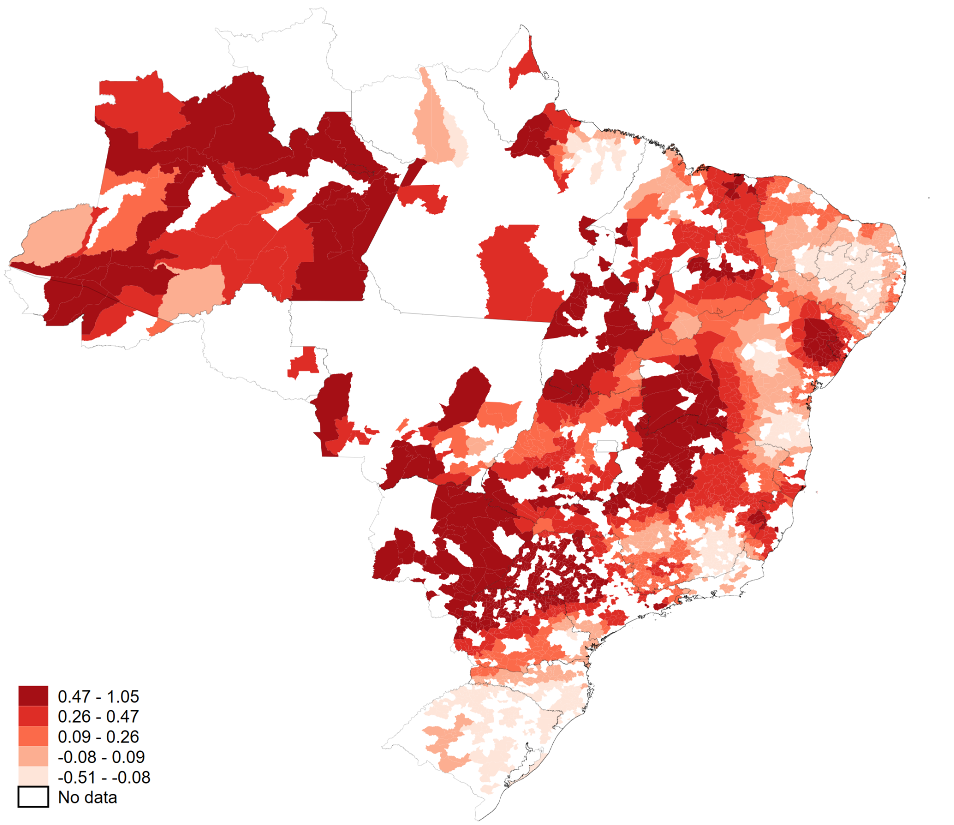
migrants are cash-constrained, the migration destinations are more likely to be more proximate and on average smaller, relative to the destinations of migrants that can afford longer displacements.

[17] In addition to assessing orthogonality the main regression controls, Table 1 also includes the results of a regression that has a lagged version of the shift-share IV (for the period 1980-1991) as the dependent variable. This variable, which we also find to be uncorrelated with the 2000-2009 shift-share shock within macroregions, is used in the robustness section of the paper to address concerns that cyclical weather patterns may introduce endogeneity.

3.4. First Stage

To further validate our approach, we assess the impact of our dryness measure on emigration out of rural areas. Figure 1 depicts the geographic variation in dryness across rural municipalities in the 2000–2009 period. It shows that, in this time frame, there were rural municipalities with unusually high dryness in most regions of the country, except for the South.

Figure 1: Variation in $-1 \times SPEI$ over the Period of Analysis



Notes: This map shows the geographic distribution of our dryness measure, defined as the monthly average of $-1 \times SPEI$ over the 2000–2009 period. Municipalities that overlap with an urban area in our sample are not included.

We use the regional variation in D_r to estimate the following regression at the rural-area level:

$$E_r = \gamma_0 + \gamma_1 D_r + \theta X_r + \mu_r \tag{3}$$

Here, E_r is the emigration rate in rural area r, during the 2001–10 period, measured as the number of working-age individuals that migrated out of municipality r in this period, expressed as a share of the population of municipality r in 1991; D_r is the average of the monthly reversed SPEI index between 2000 and 2009; X_r is a set of controls measured before 2000, and μ_r is a rural-area-level residual term. The controls include the same variables used in the city-level regressions, but measured for the rural areas of origin of migrants.

Panel A of Table 2 reports the results. Column (1) reports estimates of γ_1 in equation 3 controlling only for macroregion fixed effects, and it shows that weather variation, as captured by the SPEI, has a statistically significant effect on emigration out of rural areas. Column (2) incorporates the vector of control variables without the baseline population. The point estimate of the impact of dryness on migration changes little and remains significant at the 1 percent level. Last, Column (3) incorporates all of our controls. In this—our preferred specification—an average dryness one standard deviation higher than the historical average is associated with a 0.72 percentage-point (8.5 percent) statistically significant increase in the emigration rate of rural municipalities. This is in line with various other studies documenting rural-urban migration effects of increasing temperatures and changes in precipitation patterns in middle-income countries (for example, Cattaneo and Peri 2016).

Next, we assess the ability of our instrument in equation 2 to predict the inflows of rural migrants into cities (that is, the first stage of our main specification). Specifically, we estimate the following equation:

$$I_c = \alpha + \sigma Z_c + X_c' \mathbf{\Sigma} + \nu_c \tag{4}$$

Here, I_c, Z_c, and X_c are defined as before; α, σ, and $\mathbf{\Sigma}$ are parameters; and ν_c is the error term. Our estimates of σ are reported in Panel B of Table 2, along with exposure-robust standard errors. Our weather-based instrument Z_c predicts rural immigration rates in cities. A one-point increase in the weighted average of dryness in the historical municipalities of origin of rural–urban migrants (that is, the instrument defined in equation 2) is associated with an average 2.5 percentage-point increase in cities' immigration rates from rural municipalities of origin. In all specifications, the statistic of the multivariate F-test of excluded instruments—also calculated using exposure-robust inference following Borusyak et al. (2022)—is close to 20, suggesting that we can rule out that the instrument is weak.

Table 2: Effects of Weather Shocks on Migration

	(1)	(2)	(3)
Panel A: Effects of precipitations on rural emigration			
	Emigration rate from rural areas		
Average $-1 \times SPEI$	0.866***	0.737***	0.720***
	(0.200)	(0.194)	(0.194)
Observations	2,870	2,868	2,868
Average of dependent variable	8.527	8.520	8.520
Macrorregion fixed effects	Yes	Yes	Yes
Main controls set	No	Yes	Yes
Log population control	No	No	Yes
Panel B: Effect of weather-based IV on rural immigration			
	Rural immigration rate to cities		
SPEI-based shift-share IV	2.629***	2.721***	2.455***
	(0.598)	(0.577)	(0.559)
F statistic	19.34	22.20	19.31
Observations	454	454	454
Average of dependent variable	5.083	5.083	5.083
Macrorregion fixed effects	Yes	Yes	Yes
Main controls set	No	Yes	Yes
Log population control	No	No	Yes

Notes: The table presents results from rural-municipality-level regressions (Panel A) and city-level regressions (Panel B), both based on 2010 census data. In Panel A, rural emigration is defined as the number of emigrants leaving a rural area from 2001–2010 as a percentage of the area's 1991 population, and the drought index is the simple average of the inverted monthly SPEI for 2000–2009. In Panel B, the endogenous variable (rural immigration rate) is defined as the number of rural migrants arriving in a city during the same period as a percentage of the city's 1991 population. The instrumental variable (IV) for each city is constructed by interacting the average inverted SPEI (2000–2009) of each rural municipality of origin with the municipality's share of total rural-urban migration arriving in the city between 1982 and 1991 (see equation 2). The controls vector in column 2 includes employment shares in manufacturing, services, and government, the share of workers with college education, and population growth from 1980–1991. In Panel A, robust standard errors clustered at the microregion level are in parentheses. Panel B reports exposure-robust standard errors (Borusyak et al., 2022), also clustered at the microregion level and calculated as described in Appendix C (equation 5). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4. Results

4.1. Descriptive Facts

To first characterize the urban economies in our study, Appendix Table 1 presents cross-city averages of key characteristics of these markets. Labor-market conditions in Brazilian cities (Panel A) improved significantly between 1991 and 2010. Employment rates and real wages increased in the average local labor market, as did labor force participation. Informality rates (which include self-employment) dropped.

The average city in our sample had a total of 153 thousand residents-occupied housing units in 1991 (among those, about four percent of those units were penurious). Urban housing markets grew substantially between 1991 and 2010, and aggregate improvements in housing quality accompanied this growth (Panel B). Housing units increased by almost 60 percent and rooms by 64 percent in the average housing market. Real rents rose by 42 percent. Across cities, penurious housing units decreased by 64 percent, while low-quality housing stock grew by 23 percent and quality housing stock by 146 percent.

Appendix Table 2 sheds light on the type of migration captured by our research design by showing descriptive statistics for urban-urban migrants, rural-urban migrants from areas with moderate weather shocks, and rural-urban migrants from severe-weather areas (with dryness more than one standard deviation away from the historical average in the three years prior to migration). Rural-urban migrants were younger and less educated than urban-urban migrants, but weather-induced migrants were similar to other rural-urban migrants in age and education (Panel A). Despite similar human capital, severe-weather migrants showed weaker labor-market performance in destination cities (Panel B), suggesting a negative selection on unobservable characteristics. While other migrants had employment rates 2 to 3 percentage points above the urban average, severe-weather migrants were only 0.1 percentage points higher. Additionally, their informality rate was 1.2 percentage points above the urban average, and their average wage was just 84 percent of the urban average.

Regarding their housing situation, about half of migrants were renters, with a propensity to rent 29 percentage points above the urban average (Panel C). While urban-urban migrants paid rents 25 percent higher than the urban average, rural-urban migrants—in line with our assumption that they disproportionately demand housing in the lower quality tiers—lived in more affordable housing, with rents between 90 and 92 percent of the urban average.

4.2. Labor-market Effects

Table 3 presents the estimated effects of rural immigration (β in equation 1) on urban residents' labor market outcomes. Column (1) provides OLS estimates as a benchmark, while columns (2) through (4) present 2SLS estimates using our weather-based IV (equation 2). Column (2) reports estimates controlling only for macroregion fixed effects. Column (3) includes the rest of controls described in Section 3.2, excluding baseline population, and column (4) further adds the logarithm of the 1991 population.

Table 3: Effects of Weather-Induced Immigration on Labor-market Outcomes of Residents

	OLS (1)	IV (2)	IV (3)	IV (4)
Δ Mean Log Wages	0.008***	-0.048***	-0.045***	-0.050***
	(0.002)	(0.017)	(0.016)	(0.019)
Δ Log Total Employment	0.011***	0.024*	0.035***	0.038***
	(0.002)	(0.014)	(0.009)	(0.010)
Macroregion fixed effects	Yes	Yes	Yes	Yes
Main controls set	Yes	No	Yes	Yes
Log population control	Yes	No	No	Yes

Notes: The table reports the results of city-level regressions (N=454). The controls vector in column 2 includes employment shares in manufacturing, services, and government, the share of workers with college education, and population growth from 1980–1991. Exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in Appendix C (equation 5), are reported in parentheses. * p <0.1 , ** p < 0.05, and *** p < 0.01.

All 2SLS specifications show that inflows of rural migrants lead to slower wage growth among urban residents over the period 1991-2010, and all results are statistically significant at conventional levels. In our preferred specification (column (4)), we estimate that a one-percentage-point increase in the rural immigration rate led to 5 percent slower wage growth among residents. The positive point estimate in the OLS specification is consistent with rural-urban migrants' tendency to choose higher-wage destinations (Busso et al., 2021). It suggests that our instrumental variable strategy effectively addresses this source of endogeneity. The overall negative impact on wages of residents is in line with what we would expect from a local labor-supply shock in the presence of a downward-sloping long-run labor-demand schedule if migrant labor was, in the aggregate, a net substitute for resident labor, as discussed in Section 2.1. They also suggest that, if there was any long-run adjustment that increased labor demand and put an upward pressure on wages, it was insufficient to compensate for the short-run negative impact on wages of the positive labor supply shock. These results are similar to those from Imbert and Ulyssea (2024), who find a negative effect on wages both on the formal and informal sector. Calderón-Mejía and Ibáñez (2016) also find negative effects on urban native wages of influxes of forced migrants to Colombian cities.

We also find that rural-migrant inflows positively and significantly affected urban residents' employment. Our preferred specification suggests that a one-percentage-point higher rural immigration rate led to a 3.8 percent higher employment among this group. These positive effects—also found in Imbert and Ulyssea (2024)—are again consistent with an increased supply of net substitute workers leading to a lower wage and a higher quantity demanded of labor. Still, they could also reflect long-term adjustments in the occupational choice of residents, as discussed in Section 2.1. In Section 5 we empirically explore the role played by these other margins of adjustment.

Heterogeneity

Table 4 explores heterogeneity in labor market effects. Panel A considers differential effects by economic sector. In both services and manufacturing, we find negative effects on residents' wages and positive effects on employment. The relative size of these coefficients varies by sector. In the services sector, the negative effect on wages is more pronounced, while the effect on employment is weaker. This difference could reflect a less elastic long-run labor demand elasticity in services than in manufacturing, but it could also be explained, as discussed in Section 2.1, by residents changing industries to move away from jobs in which they are substitutes for migrant labor and towards jobs in which they are more complementary.

Table 4: Heterogeneity in the Labor-Market Effects of Weather-Induced Immigration

	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)
Panel A: By industry				
Services				
Δ Mean Log Wages	-0.001	-0.069***	-0.068***	-0.075***
	(0.002)	(0.020)	(0.019)	(0.023)
Δ Log Total Employment	0.002	0.030*	0.025**	0.029**
	(0.002)	(0.017)	(0.012)	(0.013)
Manufacturing				
Δ Mean Log Wages	0.011***	-0.044***	-0.038**	-0.042**
	(0.003)	(0.016)	(0.015)	(0.017)
Δ Log Total Employment	0.040***	0.158***	0.142***	0.149***
	(0.007)	(0.028)	(0.027)	(0.031)
Panel B: By schooling attainment				
Less than high school				
Δ Mean Log Wages	0.012***	-0.032**	-0.029**	-0.033*
	(0.002)	(0.015)	(0.014)	(0.017)
Δ Log Total Employment	0.013***	-0.013	0.000	-0.002
	(0.002)	(0.016)	(0.010)	(0.011)
High school or more				
Δ Mean Log Wages	-0.006**	-0.075***	-0.076***	-0.087***
	(0.003)	(0.021)	(0.021)	(0.025)
Δ Log Total Employment	0.003	0.046**	0.036**	0.038**
	(0.003)	(0.023)	(0.016)	(0.018)
Panel C: Among recent migrants				
Δ Mean Log Wages	0.008***	-0.060***	-0.057***	-0.063***
	(0.002)	(0.019)	(0.018)	(0.021)
Δ Log Total Employment	0.020***	-0.036	-0.029	-0.039
	(0.006)	(0.038)	(0.036)	(0.040)
Macroregion fixed effects	Yes	Yes	Yes	Yes
Main controls set	Yes	No	Yes	Yes
Log population control	Yes	No	No	Yes

Notes: The table reports the results of city-level regressions. In Panel C, recent migrants are defined as those that arrived in the city during the last five years prior to the census. For the wage measure we use the average of the residuals of an individual-level regression of the logarithm of the monthly wages on a vector of schooling attainment indicators and a vector of age categories indicators. Due to data constraints, the number of observations varies by sub-sample, with 454 for Panel A and Panel B, and 453 for Panel C. The controls vector in column 2 includes employment shares in manufacturing, services, and government, the share of workers with college education, and population growth from 1980–1991. Exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in Appendix C (equation 5), are reported in parentheses. * p <0.1 , ** p < 0.05, and *** p < 0.01.

Panel B reports heterogeneous labor market impacts of weather-induced migration by schooling attainment. We find that the long-run labor market effects of migration are stronger for residents with at least high-school than for the average. Among less educated resident workers, the wage effect is significantly smaller, and there is no employment effects. This can be interpreted, in light of the theory discussed in Section 2.1, as the result of residents' responses to the initial effects of migration. For example, residents that faced migrants' competition in the labor market could have moved to different cities, or could have pursued higher education levels. In Section 5 we present empirical evidence consistent with both of these mechanisms.

As long as local labor markets are not segmented by the migration status of workers—as we assume, following the existing evidence in the literature—weather-induced migration will affect not only the labor market outcomes of residents, but also the labor market conditions faced by migrants themselves. We explore these effects in Panel C of Table 4 by looking at the outcomes of recent migrants, defined as those that arrive in the city during the last five years prior to the census.[18] Since recent migrants have had limited time to adjust, these results are likely to capture primarily partial, short-term effects. We find that the wages earned by recent migrants grew slower over the period of analysis in cities with higher rural-urban migration, while their overall employment growth was unaffected. These results are consistent with stronger wage effects in the short run that may be later mitigated by further labor market adjustments. They also suggest that the higher quantities of labor demanded as a result of the negative wage effects accrue disproportionately to residents rather than to migrants in the short run.

4.3. Housing-market Effects

We now turn to the effects of weather-induced migration on residents' housing-market outcomes. Table 5 reports the effects on prices and quantities for residents-occupied urban housing units, using the same specifications as in our labor markets analysis. The results show that migrant inflows increase local housing demand, pushing prices up. A one-percentage-point higher rural immigration rate led, in our preferred specification, to a 6.1 percent increase in housing rents (adjusted for housing characteristics). In a related study—looking at the impact of war-driven Syrian refugees in Jordan—Rozo and Sviatschi (2021) also find a positive effect of forced immigration on rents. Our estimates of the quantity effects are also

[18]We focus on recent migrants because, as year pass after the migration event, migrants are more likely to settle in and behave more like residents. Note that workers considered migrants in 1991 are treated as residents in 2010 if they remain in the city, so that there is no overlap in the populations for which we compute the 1991 and 2010 outcomes.

positive and significant, suggesting that a one-percentage-point increase in rural immigration led to a 3.6 percent increase in the total number of housing units and a 4.5 percent increase in the total number of rooms.

Table 5: Effects of Weather-Induced Immigration on the Local Housing-market of Residents

	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)
Δ Mean Log Housing Rents	-0.015**	0.061***	0.054***	0.061***
	(0.006)	(0.023)	(0.020)	(0.023)
Δ Log Total Number of Housing Units	0.008***	0.028***	0.033***	0.036***
	(0.002)	(0.010)	(0.007)	(0.008)
Δ Log Total Number of Rooms	0.007***	0.037***	0.041***	0.045***
	(0.002)	(0.011)	(0.009)	(0.010)
Macroregion fixed effects	Yes	Yes	Yes	Yes
Main controls set	Yes	No	Yes	Yes
Log population control	Yes	No	No	Yes

Notes: The table reports the results of city-level regressions (N=453). City aggregates are computed directly from the census microdata as averages across households in which the head of household was a non-migrant resident. The controls vector in column 2 includes employment shares in manufacturing, services, and government, the share of workers with college education, and population growth from 1980–1991. Exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in Appendix C (equation 5), are reported in parentheses. * p <0.1 , ** p < 0.05, and *** p < 0.01.

Heterogeneity

Table 6 shows that these aggregate effects mask important heterogeneity.[19] The influx of rural migrants appears to have disproportionate increased demand for penurious housing, to the detriment of demand growth for low-quality and quality housing. This resulted in an overall downgrading of housing quality in urban areas receiving migrants—or more precisely, to a slower improvement in housing quality over the 1991–2010 period.

[19] Appendix Table 3 shows the effects of weather-induced immigration on the local housing market of residents *and* migrants. Results are similar to those presented in Tables 5 and 6.

Table 6: Heterogeneity in the Housing-Market Effects of Weather-Induced Immigration

	OLS (1)	IV (2)	IV (3)	IV (4)
Panel A: Penurious housing				
Δ Mean Log Housing Rents	-0.040**	-0.046	-0.078	-0.071
	(0.020)	(0.060)	(0.054)	(0.063)
Δ Log Total Number of Housing Units	0.061***	0.289***	0.287***	0.313***
	(0.023)	(0.090)	(0.084)	(0.106)
Δ Log Total Number of Rooms	0.053**	0.306***	0.308***	0.339***
	(0.025)	(0.096)	(0.089)	(0.113)
Panel B: Low-quality housing				
Δ Mean Log Housing Rents	-0.021***	0.075***	0.065***	0.071***
	(0.007)	(0.027)	(0.024)	(0.026)
Δ Log Total Number of Housing Units	-0.026***	-0.077**	-0.079***	-0.080**
	(0.005)	(0.035)	(0.029)	(0.033)
Δ Log Total Number of Rooms	-0.024***	-0.055	-0.058**	-0.057*
	(0.005)	(0.035)	(0.029)	(0.031)
Panel C: Quality housing				
Δ Mean Log Housing Rents	-0.016***	0.026	0.041	0.050
	(0.004)	(0.025)	(0.030)	(0.036)
Δ Log Total Number of Housing Units	-0.020	-0.144	-0.149	-0.173
	(0.014)	(0.090)	(0.096)	(0.117)
Δ Log Total Number of Rooms	-0.020	-0.144	-0.147	-0.168
	(0.014)	(0.090)	(0.095)	(0.115)
Panel D: Among recent migrants				
Δ Mean Log Housing Rents	-0.017***	0.033	0.023	0.029
	(0.003)	(0.021)	(0.020)	(0.023)
Δ Log Total Number of Housing Units	0.015***	-0.069*	-0.061*	-0.074*
	(0.005)	(0.039)	(0.036)	(0.041)
Δ Log Total Number of Rooms	0.011*	-0.105**	-0.095**	-0.109**
	(0.005)	(0.045)	(0.040)	(0.047)
Macroregion fixed effects	Yes	Yes	Yes	Yes
Main controls set	Yes	No	Yes	Yes
Log population control	Yes	No	No	Yes

Notes: The table reports the results of city-level regressions. City aggregates are computed directly from the census microdata as averages across households in which the head of household was a non-migrant resident. We define housing quality using a vector of four housing attributes that are consistently observable across censuses: sewage network, trash collection, brick walls, and water network. If a house is missing all four of these attributes, it is classified as penurious, and if it is missing at least one, low quality. Houses that are not missing any of these attributes are classified as quality housing. For Panel D, we only considered households where the head of the household is a recent migrant, defined as those that arrived in the city during the last five years prior to the census. Due to data constraints, the number of observations varies by sub-sample, corresponding to 166, 450, 299, and 452 for penurious, low-quality, quality housing units, and among recent migrants, respectively. The controls vector in column 2 includes employment shares in manufacturing, services, and government, the share of workers with college education, and population growth from 1980–1991. Exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in Appendix C (equation 5), are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Specifically, our preferred specification shows that, in the penurious housing category, a one-percentage-point increase in rural immigration led to an 31 percent significant increase in housing units and a 33 percent significant increase in the number of rooms, with no effect on housing rents.[20] These results suggest that rural-urban migrants disproportionately shifted the demand toward penurious housing, where the housing supply is highly elastic. This is consistent with the findings in Cavalcanti et al. (2019), who show that rural-urban migration is a key determinant of slum formation.

In contrast, in the next-higher housing category (low quality), we observe that rural migration led to faster growth in housing rents and slower growth in resident-occupied housing quantities. Our preferred specification shows that, in this category, a one-percentage-point increase in the rural immigration rate led to a 7.1 percent greater increase in housing rents, accompanied by an 8 percent slower increase in the number of housing units and a 5.7 percent slower increase in the number of rooms. These effects are significant at conventional levels. Similar point estimates for wages, and even larger estimates for quantities, are observed in the quality housing category, although these estimates are not statistically significant. These results are consistent with what we would expect from an increase in housing demand in the presence of a relatively inelastic housing supply.

Taken together, our results are consistent with the hypothesis discussed in Section 2.2 that lower-quality housing "squeezes" the development of higher-quality units on scarce urban land (Brueckner and Selod, 2009), and that a low rate of conversion from low- to high-quality housing over time (Henderson et al., 2021) results in slower overall upgrading of housing quality in the long run in cities with high inflows of rural-urban migrants. With scarcer and less affordable housing in the higher-quality tiers, some residents appear to have opted for the lowest housing quality tier.

In the final panel of Table 6, we re-estimate the effects of migration on aggregate housing outcomes, focusing only on housing units occupied by recent migrants from two different cohorts: 1991 and 2010. The results show no statistically significant effects on housing rents and a negative effect on housing quantities. When we analyze each housing quality segment separately (Appendix Table 4), we find that the aggregate results are primarily driven by the middle-tier segment ("low-quality housing"). Compared to earlier migrant cohorts, newer generations of migrants occupied this type of housing at a lower rate. The point estimates for housing quantities are also negative—though not statistically significant—in the other housing segments, suggesting that in cities receiving larger rural-to-urban migration flows,

[20] These effects are large in percentage terms. However, it should be noted that they are based on relatively small initial quantities: the average city in our sample had a total of 153 thousand residents-occupied housing units in 1991, with 560 classified as penurious (Appendix Table 1).

recent migrants in 2010 lived in more overcrowded conditions than recent migrants in 1991.

4.4. Robustness

Next, we assess the robustness of our results against potential threats to the validity of our empirical strategy. Table 7 reports these tests for our main labor-market and housing-market results. Appendix Tables 5 and 6 do the same for our heterogeneity results in both of these markets. In all three, Column (1) reproduces, as a reference, the results of our preferred specification.

Table 7: Robustness Tests of the Effects of Weather-Induced Immigration on Labor-market and Housing-market Outcomes of Residents

	Baseline results (1)	Population growth control (2)	Commuting time control (3)	Clustered SE Mesoregion (4)	Absolute value of SPEI as instrument (5)	Lagged shocks control (6)
Panel A: Labor Market outcomes						
Δ Mean Log Wages	-0.050***	-0.059**	-0.050***	-0.050*	-0.105*	-0.048***
	(0.019)	(0.024)	(0.019)	(0.029)	(0.058)	(0.018)
Δ Log Total Employment	0.038***	0.037***	0.039***	0.038**	0.047**	0.037***
	(0.010)	(0.012)	(0.010)	(0.016)	(0.019)	(0.010)
Panel B: Housing Market outcomes						
Δ Mean Log Housing Rents	0.061***	0.067**	0.060***	0.061*	0.031	0.063***
	(0.023)	(0.028)	(0.023)	(0.035)	(0.047)	(0.022)
Δ Log Total Number of Housing Units	0.036***	0.036***	0.036***	0.036***	0.041**	0.035***
	(0.008)	(0.010)	(0.008)	(0.012)	(0.018)	(0.008)
Δ Log Total Number of Rooms	0.045***	0.046***	0.045***	0.045***	0.039**	0.044***
	(0.010)	(0.012)	(0.010)	(0.015)	(0.018)	(0.010)
Macroregion fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Main controls set	Yes	Yes	Yes	Yes	Yes	Yes
Log population control	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the results of city-level regressions. All columns include macroregion fixed effects, the main controls set, and the logarithm of the 1991 population. Average commute time (column 3) is estimated based on midpoints of the time intervals available in the census. In column 5, the IV is constructed by interacting the absolute value of the SPEI (2000–2009) of each rural municipality of origin with the share of migrants from that municipality in total rural-urban migration to a city from 1982 to 1991. Column 6 adds the lagged shift-share instrument for the 1981-1990 period as a control. In all columns, exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in equation 5, are reported in parentheses, except for column 4, where they are clustered at the mesoregion level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

First, as discussed in Section 2.1, the expansion of the local workforce due to migration can increase residents' wages through agglomeration effects, potentially biasing estimates of migration's impact on labor market outcomes unless these effects are properly accounted for. Combes et al. (2015) suggest that, in a static framework, one way to mitigate this concern is to directly control for the overall size of the city. We implement a long-differences version of this approach by adding the log growth of the city's population over the period 1991-2010 to our main set of controls. The results are reported in column (2). All of our main results remain unchanged after introducing this control. In the labor market, the estimates of migration's effects on residents' wages and employment remain very similar in size and significance, both in aggregate and when calculated separately for industry and skill subgroups, as well as for recent migrants. This suggests that our estimates are not biased by migration-driven agglomeration effects. The same holds for the housing market, where all estimates remain of similar size and direction, though a few quantity results become less precisely estimated.

A second concern is how cross-city differences in spatial configuration may affect the results. While our housing rents measure controls for variation in dwelling characteristics, it does not account for a key price determinant: dwelling location. Specifically, as noted by Combes et al. (2019), prices of comparable housing units can vary significantly within a city, depending on their distance from job centers and other neighborhood attributes. The location of residences within a city can also impact labor market outcomes by affecting workers' ability to access suitable job opportunities. In column (3) of our robustness tables, we include the city's average commuting time as a control.[21] The results are nearly identical, suggesting that the relevant variation in housing characteristics is already captured by our residual rents measure.

Our main inference procedure relies on exposure-robust standard errors clustered at the microregion level. Microregions may not be, however, a large enough geographic area to account for the potential spatial autocorrelation of weather shocks. In Column (4) we assess the robustness to an even more conservative clustering approach. Specifically, we allow for arbitrary correlation of the error terms of localities in the same mesoregion. Mesoregions are geographic units larger than microregions but smaller than macroregions. As in our other analyses, we adjust mesoregion boundaries to make them time consistent, resulting in a total of 122 clusters. As expected, all our estimations lose some precision but overall remain statistically significant at conventional confidence levels. This suggests that the exposure-robust standard errors clustered at the microregion level that we use in our main results adequately address inference concerns arising from spatially autocorrelated weather shocks.

Another issue is whether our focus on "excess dryness" as an expulsion shock for rural-urban migrants emphasizes the most relevant source of exogenous variation. Specifically,

[21] Commuting data is only available in the 2010 census and is reported in time intervals. We estimate the average commuting time using the midpoints of these intervals. Estimates for housing quality subgroups in Appendix Table 6 use the average commuting times of residents within each housing category as a control.

"excess wetness" can also lead to floods, agricultural plagues, and other challenges, potentially increasing rural migration to cities. Appendix Figure 1 shows the distribution of our dryness measure (the inverted SPEI) across Brazilian rural municipalities, illustrating that deviations from historical averages are more frequent on the "dry" side than on the "wet" side of the distribution during the period analyzed. Even though excess wetness is less frequent, it may still have a stronger impact on migration than droughts. To investigate this, we calculate an alternative version of our instrument, using the absolute deviations from historical SPEI means instead of excess dryness deviations. While this version of the weather shock remains strongly predictive of rural emigration, the shift-share IV constructed with this variation proves to be a weak instrument for city-level rural immigration rates, with the multivariate F-test statistic for excluded instruments consistently below 10 (Appendix Table 7). Consequently, when we rerun our regressions using this instrument (column (5) in the robustness tables), the estimates become noisier, though the direction and magnitude of the results remain entirely consistent with those from our main instrument.

An additional source of concern is the fact that precipitation patterns are influenced by El Niño Southern Oscillation (ENSO), which is cyclical. The last major ENSO event that could have affected the evapotranspiration conditions captured by the SPEI—and, in consequence, migration—during our period of analysis (i.e., the 1997-1998 event) may have disproportionately affected the same places as the prior major ENSO event (1982-1983). This may bias our results, as the effect we observe may be driven both by historical and current migration shocks, as highlighted by Jaeger, A et al. (2019).[22] To address this concern, we calculate a lagged shift-share instrument for the 1980-1991 period. We included the lagged instrument in the balance tests reported in Table 1 finding that, conditional on macroregion fixed effects, the lagged instrument is not correlated with the instrument used in our estimations (corresponding to the period 2000-2009). In column (6) of Table 7 and Appendix Tables 5 and 6, we recalculate our main results, including the lagged instrument in the vector of controls. All estimates are minimally altered, maintaining their size and statistical significance.

[22] Cyclical variation in precipitation can also introduce endogeneity in the shares component of the instrument, since rural municipalities previously affected by an ENSO event may end up having a larger share of the total rural immigrants in destination cities. However, this is less of a concern in our application because the quasi-experimental framework of Borusyak et al. (2022) allows for shares to be endogenous without compromising the consistency of the estimator.

Two-stage Estimation Approach

The fact that we construct city-level outcomes from individual data can raise additional concerns, as cities differ in population composition. Workers may have varying skill sets, and housing units can differ significantly in size and construction materials across cities. Consequently, price differences between cities may partly reflect these compositional variations. In our main specification, we address this issue by using the residuals from individual-level regressions of wages and housing rents on observable individual characteristics (education and experience for wages, and housing unit characteristics for rents). We then take the averages of these residuals as city-level outcomes. However, this approach relies on an important implicit assumption: that the role of location is orthogonal to the influence of individual characteristics. In practice, this assumption may be too strong, as it overlooks the possibility of sorting, which could result in unobserved individual heterogeneity being correlated with both migrants' location choices and residents' outcomes (Combes et al., 2015). For example, rural-urban migrants may be disproportionately drawn to cities with large shares of highly skilled residents, whose skills complement those of the migrants, or to cities with a larger supply of low-tier, affordable housing.

To address this issue, we follow Combes et al. (2008) and implement a two-stage procedure. In the first stage, we estimate individual-level regressions that include both individual characteristics and city fixed effects, separately for each of the two census rounds (1991 and 2010). The estimated fixed effects capture the city-specific premium in wages or rents, controlling for the individual characteristics of workers and dwellings at each point in time. In the second stage, we use the long difference of these fixed effects (across the two census rounds) as outcomes in equation 1, estimated using our shift-share instrumentation approach. It is important to note that we can only apply this procedure to prices, as quantities (such as employment and the total number of housing units and rooms) are city-level outcomes rather than individual-level ones.

The results obtained using this approach are reported in Table 8. In both the labor and housing markets, the estimated effects of rural-urban migration are very similar to those from our main specification, both in terms of the size of the point estimates and their significance. This suggests that sorting is not a significant source of bias in our context.

Table 8: Two-state Estimation of Effects of Weather-Induced Immigration on Labor-market and Housing-market Outcomes of Residents

	OLS (1)	IV (2)	IV (3)	IV (4)
Panel A: Wages				
Δ City Fixed Effect (Log Wages Equation)	0.008***	-0.045***	-0.043***	-0.048***
	(0.002)	(0.016)	(0.016)	(0.018)
Services				
Δ City Fixed Effect (Log Wages Equation)	-0.001	-0.068***	-0.066***	-0.074***
	(0.002)	(0.019)	(0.018)	(0.022)
Manufacturing				
Δ City Fixed Effect (Log Wages Equation)	0.011***	-0.042***	-0.037**	-0.041**
	(0.003)	(0.016)	(0.015)	(0.017)
Less than high school				
Δ City Fixed Effect (Log Wages Equation)	0.012***	-0.030**	-0.028**	-0.031*
	(0.002)	(0.015)	(0.014)	(0.016)
High school or more				
Δ City Fixed Effect (Log Wages Equation)	-0.006**	-0.075***	-0.075***	-0.084***
	(0.003)	(0.021)	(0.020)	(0.024)
Among recent migrants				
Δ City Fixed Effect (Log Wages Equation)	0.007***	-0.058***	-0.054***	-0.060***
	(0.002)	(0.019)	(0.017)	(0.020)
Panel B: Housing Rents				
Δ City Fixed Effect (Log Rents Equation)	-0.015**	0.051**	0.044**	0.051**
	(0.006)	(0.021)	(0.019)	(0.021)
Penurious housing				
Δ City Fixed Effect (Log Rents Equation)	-0.041**	-0.055	-0.086	-0.080
	(0.020)	(0.061)	(0.055)	(0.064)
Low-quality housing				
Δ City Fixed Effect (Log Rents Equation)	-0.022***	0.055**	0.046**	0.050**
	(0.007)	(0.023)	(0.021)	(0.023)
Quality housing				
Δ City Fixed Effect (Log Rents Equation)	-0.017***	0.026	0.040	0.049
	(0.004)	(0.025)	(0.030)	(0.036)
Among recent migrants				
Δ City Fixed Effect (Log Rents Equation)	-0.015***	0.030	0.021	0.027
	(0.003)	(0.020)	(0.019)	(0.022)
Macroregion fixed effects	Yes	Yes	Yes	Yes
Main controls set	Yes	No	Yes	Yes
Log population control	Yes	No	No	Yes

Notes: The table presents the results of city-level regressions. Following Combes et al. (2008), we first estimate city fixed effects separately for 1991 and 2010 using the regression $Y_i = X_i\alpha + \delta_{c(i)} + \epsilon_i$, where Y_i is the individual-level outcome, $\delta_{c(i)}$ represents city fixed effects, and X_i is a vector of individual characteristics. In the wage regressions, X_i includes education and experience, while in the rents regressions, it includes the logarithm of the number of rooms, access to the main sewage system, and trash collection services. In the second stage, we apply our instrumentation strategy to estimate equation 1, where the outcomes are the differences in the fixed effects of the variable of interest between the two census rounds. For the subgroup specification, the first stage regression includes interaction terms between the city fixed effects and the binary variables for each category, along with the vector of individual/unit characteristics. The controls in column 2 include employment shares in manufacturing, services, and government, the share of workers with college education, and population growth from 1980–1991. Exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in Appendix C (equation 5), are reported in parentheses. * p <0.1 , ** p < 0.05, and *** p < 0.01.

5. Other Effects on Local Economies

The reduced-form results discussed in the prior section capture the long-term effects of migration on urban labor and housing markets. As noted in Section 2, these reflect not only the partial, short-term effects predicted by standard theory but also the additional effects resulting from local agents' responses to the initial partial effects. In this section, we consider additional outcomes that provide insight into the role such second-order effects may have played in our context. Tables 9 and 10 report estimates of the effects of migration on these outcomes, calculated using the same specification and instrumentation strategy as in our main results.

5.1. Additional Effects on Local Labor Markets

One possibility is that if migration had a partial effect on residents' wages, it may have also influenced their incentives to participate in the labor market. Lower wages could have reduced labor force participation among residents, and the resulting smaller labor supply could have attenuated or even reversed the initial negative effect on wages, as well as any positive effect on employment. For example, Dustmann et al. (2017) find that the inflow of Czech workers into border regions in Germany led to a small decrease in native wages and a significant drop in native employment, largely driven by reduced inflows of natives into the workforce. Conversely, if migration initially raised wages, it could have increased labor force participation, tempering wage increases and amplifying any positive employment effects. Panel A of Table 9 assesses the impact of migration on residents' labor force participation in Brazilian cities. We find no significant effects, suggesting that our long-term results were not significantly influenced by this margin of adjustment.

Another way in which residents could have responded to the initial effects of migration is by reducing their participation in industries where they faced competition from migrant workers and/or increasing their participation in industries where their labor was more complementary (Peri, 2016). These shifts would have acted as a negative labor supply shock in industries where migrants were substitutes for residents, or as a positive supply shock in industries where both groups of workers were complementary. Recall that, as shown in Panel A of Table 4, while migration had negative effects on wages and positive effects on employment in both services and manufacturing, the wage effects were significantly larger in services, whereas the employment effects were more pronounced in manufacturing. In Table 9 (Panel B), we complement these results by evaluating the effects of migration on the share of each industry in residents' employment. We find that a one-percentage-point increase in the rural immigration rate had no effect on the services share, but a positive 1.7-percentage-point effect on the manufacturing share in our preferred specification. Taken together, these results suggest that migration led to increased participation of residents in manufacturing industries.

Table 9: Effects of Weather-Induced Immigration on Other Labor-market Outcomes of Residents

	OLS (1)	IV (2)	IV (3)	IV (4)
Panel A: Participation rates				
Δ Labor Force Participation Rate	0.004***	0.000	0.002	0.002
	(0.001)	(0.003)	(0.003)	(0.003)
Panel B: Participation in specific sectors				
Δ Share of Employment in Services	-0.004***	0.005	-0.000	0.001
	(0.001)	(0.004)	(0.003)	(0.003)
Δ Share of Employment in Manufacturing	0.005***	0.020***	0.017***	0.017***
	(0.001)	(0.004)	(0.004)	(0.004)
Panel C: Emigration effect				
Emigration Rate 2000-2010	0.000	0.018**	0.019***	0.015**
	(0.001)	(0.007)	(0.007)	(0.007)
Panel D: Share of workers with high-school				
Δ Share with high school or more	0.000	0.021***	0.021***	0.024***
	(0.001)	(0.004)	(0.005)	(0.005)
Panel E: Informality rates				
Δ Informality Rate (including self-employment)	-0.004***	-0.017***	-0.014***	-0.015***
	(0.001)	(0.005)	(0.004)	(0.004)
Δ Informality Rate	-0.006***	-0.011***	-0.013***	-0.013***
	(0.001)	(0.004)	(0.004)	(0.004)
Macroregion fixed effects	Yes	Yes	Yes	Yes
Main controls set	Yes	No	Yes	Yes
Log population control	Yes	No	No	Yes

Notes: The table reports the results of city-level regressions (N=454). Dependent variables are the difference in the outcome of interest for residents in a given city between 1991 and 2010. In Panel C, the dependent variable is the emigration rate between 2000 and 2010. The controls vector in column 2 includes employment shares in manufacturing, services, and government, the share of workers with college education, and population growth from 1980–1991. Exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in Appendix C (equation 5), are reported in parentheses. * p <0.1 , ** p < 0.05, and *** p < 0.01.

Another possible response of residents to the inflow of migrants is to move away from the city. Boustan et al. (2010) finds evidence of such effects in U.S. cities during the Great Depression, although many studies do not observe significant geographic mobility responses (Peri, 2016). In Panel C, we evaluate the effects of rural immigration on the emigration rate of city residents and find positive and significant effects.[23] These responses may have moderated the initial negative effects on wages and the positive effects on employment among resident workers who remained in the city and whose skills were complementary to those of migrant workers.

Residents could have also become more complementary to migrants in the labor market by upgrading their skills. For example, Hunt (2017) finds that a one-percentage-point increase in international migrants to the U.S. led to a 0.3 percentage-point increase in the probability of natives completing 12 years of schooling. In Panel D of Table 9, we measure the effect of migration on the share of residents who have completed high school education and find a positive effect. A one-percentage-point increase in the rural immigration rate is associated with a 0.024 percentage-point increase in the likelihood of a resident having completed at least secondary education. As discussed in Section 2.1, since migrants were generally less educated and low-skilled workers tended to complement rather than substitute high-skilled workers, residents' skill upgrading may have mitigated the negative impact of migration on wages.

Next, we investigate the effects of rural migration on urban labor informality rates (Table 9, Panel E). As discussed in Section 2.1, even under the assumption that formal and informal jobs are filled by workers from a single labor pool, migration is likely to increase informality and dampen wage growth in the short run, as informal labor demand is typically more elastic than formal labor demand. The long-run effects, however, depend on the role of informal labor markets in local economies. As discussed by Imbert and Ulyssea (2024), informality can have two contrasting effects. On the one hand, informality may allow less productive firms to survive by competing with more productive formal firms, leading to persistently higher long-run informality rates. On the other hand, the informal sector can serve as a "stepping stone" for high-growth-potential firms, which eventually formalize, increasing formal labor demand and reducing informality. Consistent with the second effect dominating the first, Imbert and

[23] As with other variables using information on the origin and destination of migrants, migration data is only available for the period 2001-2010. Emigration rates are constructed by expressing the number of migrants who reported moving away from the city during this period as a share of the city's population in the 2000 census.

Ulyssea (2024) find that in Brazil, rural-urban migration had a *negative* long-run effect on urban informality rates. Our results align with this finding: a ten-percentage-point increase in rural migration rates in our sample led to a 0.13 percentage-point drop in informality rates. These results are not driven by self-employed individuals, as the estimates remain very similar when we exclude this group from the definition of informal workers and instead focus solely on individuals who do not have a "signed work booklet" – the most commonly used definition in Brazilian labor literature.

5.2. Additional Effects on Local Housing markets Markets

Lastly, we examine how the adjustment of urban housing markets to rural migration affected homeownership rates. Consistent with theory (Section 2.2), the relatively lower availability and affordability of higher-tier housing appear to have reduced homeownership rates in high-migration cities. As shown in Table 10, migration led to a smaller proportion of housing units being owner-occupied. This increased propensity to rent is observed in both "low-quality" and "high-quality" units and affected both resident-occupied and migrant-occupied units similarly. Together with the evidence discussed in Section 4.3, our results suggest that, in the long run, the partial effects of migration on the affordability of higher-tier housing units in high-migration cities were amplified by both slower development and an increased conversion from owner-occupied to rental units in these segments.

Table 10: Effects of Weather-Induced Immigration on Other Housing-market Outcomes

	OLS (1)	IV (2)	IV (3)	IV (4)
Panel A: All housing units				
Δ Residents' and Migrants' Ownership Rate	-0.010***	-0.042***	-0.043***	-0.046***
	(0.002)	(0.009)	(0.008)	(0.009)
Δ Residents' Ownership Rate	-0.008***	-0.047***	-0.046***	-0.049***
	(0.002)	(0.010)	(0.009)	(0.011)
Panel B: By housing quality				
Penurious housing				
Δ Residents' and Migrants' Ownership Rate	-0.021***	-0.009	-0.008	-0.007
	(0.002)	(0.013)	(0.013)	(0.014)
Δ Residents' Ownership Rate	-0.014***	-0.011	-0.011	-0.009
	(0.004)	(0.012)	(0.012)	(0.013)
Low-quality housing				
Δ Residents' and Migrants' Ownership Rate	-0.008***	-0.045***	-0.044***	-0.047***
	(0.001)	(0.010)	(0.008)	(0.010)
Δ Residents' Ownership Rate	-0.007***	-0.049***	-0.047***	-0.051***
	(0.002)	(0.011)	(0.009)	(0.011)
Quality housing				
Δ Residents' and Migrants' Ownership Rate	-0.007***	-0.072***	-0.075***	-0.089***
	(0.002)	(0.018)	(0.020)	(0.027)
Δ Residents' Ownership Rate	-0.006***	-0.080***	-0.082***	-0.098***
	(0.002)	(0.018)	(0.019)	(0.026)
Macroregion fixed effects	Yes	Yes	Yes	Yes
Main controls set	Yes	No	Yes	Yes
Log population control	Yes	No	No	Yes

Notes: The table reports the results of city-level regressions. City aggregates are computed directly from the census microdata as averages across households. Due to data constraints, the number of observations varies by sub-sample, with 454 in Panel A, and 415, 403, 454, 454, 326, and 320 in Panel B, corresponding to each row, respectively. The controls vector in column 2 includes employment shares in manufacturing, services, and government, the share of workers with college education, and population growth from 1980–1991. Exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in Appendix C (equation 5), are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

6. Conclusion

Climate change is likely to increase the severity and frequency of weather-related shocks. From droughts to hurricanes to wildfires, these events can harm the livelihoods of rural households (especially those who are the most vulnerable), causing them to migrate to other destinations. In this paper, we studied the impact that these migrants have on the labor and housing markets' outcomes of residents in their destination cities.

Our results show significant long-term impacts of weather-induced rural-urban migration on both labor and housing markets in Brazilian cities. In the labor market, we find that higher rural immigration led to slower wage growth but faster employment growth among urban residents over the 1991-2010 period, consistent with a long-run downward-sloping local labor demand curve. In the housing market, rural migration resulted in faster growth of both prices and quantities. Importantly, the effects on housing quantities were largest in the lowest quality segment, while price effects were strongest in higher quality tiers. This pattern suggests that rural-urban migration slowed down overall housing quality upgrading in destination cities.

These long-run estimates reflect not only the direct, short-run impact of immigration on labor and housing markets, but also the effects of residents' responses to these initial shocks. We find evidence for several important adjustment mechanisms, including increased emigration of residents to other cities, upgrades in educational attainment, and shifts in industry composition of employment. These endogenous responses help explain why the long-run effects differ from what standard models would predict based solely on the initial labor supply shock. Our findings highlight the importance of considering both short-term impacts and long-term adjustments when studying the effects of migration.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT in order to perform selected spelling, grammar, and vocabulary checks. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

Adão, R., Kolesár, M., Morales, E., 2019. Shift-Share Designs: Theory and Inference. Quarterly Journal of Economics 134 (4), 1949–2010.

Albert, C., Bustos, P., Ponticelli, J., 2024. The Effects of Climate Change on Labor and Capital Reallocation. NBER Working Paper 28995.

Altonji, J. G., Card, D., 1991. The effects of immigration on the labor market outcomes of less-skilled natives. In: Immigration, Trade and the Labor Market. No. January. Ch. 7, pp. 201 – 234.

Alves, G., 2021. Slum growth in Brazilian cities. Journal of Urban Economics 122 (October 2018), 103327.

Bartik, T. J., 1991. Who Benefits from State and Local Economic Development Policies? Books from Upjohn Press, Kalamazoo.

Berger, D., Guerrieri, V., Lorenzoni, G., Vavra, J., 2018. House prices and consumer spending. Review of Economic Studies 85 (3), 1502–1542.

Blanchard, O. J., Katz, L. F., 1992. Regional Evolutions. Brookings Papers on Economic Activity 1992 (1).

Borusyak, K., Hull, P., Jaravel, X., 2022. Quasi-Experimental Shift-Share Research Designs. Review of Economic Studies 89 (1), 181–213.

Boustan, L. P., Fishback, P. V., Kantor, S., 2010. The Effect of Internal Migration on Local Labor Markets: American Cities during the Great Depression. Journal of Labor Economics 28 (4), 719–746.

Brueckner, J. K., Mation, L., Nadalin, V. G., 2019. Slums in Brazil: Where are they located, who lives in them, and do they 'squeeze' the formal housing market? Journal of Housing Economics 44 (January), 48–60.

Brueckner, J. K., Selod, H., 2009. A Theory of Urban Squatting and Land-Tenure Formalization in Developing Countries. American Economic Journal: Economic Policy 1 (1), 28–51.

Busso, M., Carrillo, P. E., Chauvin, J. P., 2023. Rethinking Urban Migration: Policy Options for Cities in Latin America and the Caribbean. Tech. rep., Inter-American Development Bank, Washington D.C.

Busso, M., Chauvin, J. P., Herrera L., N., 2021. Rural-urban migration at high urbanization levels. Regional Science and Urban Economics 91 (February).

Busso, M., Fazio, M. V., Levy, S., 2012. (In)formal and (un)productive: The productivity costs of excessive informality in Mexico. IDB Working Paper NO. IDB-WP-341.

Calderón-Mejía, V., Ibáñez, A. M., 2016. Labour market effects of migration-related supply shocks: Evidence from internal refugees in Colombia. Journal of Economic Geography 16 (3), 695–713.

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

Cattaneo, C., Peri, G., 2016. The migration response to increasing temperatures. Journal of Development Economics 122, 127–146.

Cavalcanti, T., Da Mata, D., Santos, M., 2019. On the Determinants of Slum Formation. Economic Journal 129 (621), 1971–1991.

Chauvin, J. P., 2018. Gender-Segmented Labor Markets and the Effects of Local Demand Shocks. Working Paper.

Combes, P. P., Démurger, S., Li, S., 2015. Migration externalities in Chinese cities. European Economic Review 76, 152–167.

Combes, P. P., Duranton, G., Gobillon, L., 2008. Spatial wage disparities: Sorting matters! Journal of Urban Economics 63 (2), 723–742.

Combes, P. P., Duranton, G., Gobillon, L., 2019. The costs of agglomeration: House and land prices in French cities. Review of Economic Studies 86 (4), 1556–1589.

Combes, P.-P. P., Gobillon, L., 2015. The Empirics of Agglomeration Economies. In: Duranton, G., Henderson, J., Strange, W. C. (Eds.), Handbook of Regional and Urban Economics, Volume 5, 1st Edition. Vol. 5. North Holland, Ch. 5, pp. 247–348.

Corbi, R., Ferraz, T., Narita, R., 2023. Internal Migration and Labor Market Adjustments in the Presence of Nonwage Compensation. Manuscript, Department of Economics, University of Sao Paulo.

Dell, M., Jones, B. F., Olken, B. A., 2012. Temperature shocks and economic growth: Evidence from the last half century. American Economic Journal: Macroeconomics 4 (3), 66–95.

Dell, M., Jones, B. F., Olken, B. A., 2014. What do we learn from the weather? The new climate-economy literature. Journal of Economic Literature 52 (3), 740–798.

Dix-Carneiro, R., Kovak, B. K., 2017. Trade Liberalization and Regional Dynamics. American Economic Review 107 (10), 2908–46.

Dustmann, C., Schonberg, U., Stuhler, J., Schönberg, U., Stuhler, J., 2017. Labor Suppy Shocks, Native Wages, and the Adjustment of Local Employment. Quarterly Journal of Economics 132 (September), 435–483.

Glaeser, E. L., 2008. Cities, Agglomeration and Spatial Equilibrium. Oxford University Press, New York.

Goldsmith-Pinkham, P., Sorkin, I., Swift, J., 2020. Bartik Instruments: What, When, Why, and HowGoldsmith-Pinkham. American Economic Review 110 (January), 2586–2624.

Guedes, R., Iachan, F. S., Sant'Anna, M., 2023. Housing supply in the presence of informality. Regional Science and Urban Economics 99, 103875.

Henderson, J. V., Regan, T., Venables, A. J., 2021. Building the City: From Slums to a Modern Metropolis. Review of Economic Studies 88 (3), 1157–1192.

Hunt, J., 2017. The impact of immigration on the educational attainment of natives. Journal of Human Resources 52 (4), 1060–1118.

Ibañez, A. M., Quigua, J., Romero, J., Velásquez, A., 2022. Responses to Temperature Shocks: Labor Markets and Migration Decisions in El Salvador. IDB working paper No. IDB-WP-1268.

IBGE, 2016. Arranjos Populacionais e Concentrações Urbanas do Brasil, 2nd Edition. IBGE, Rio de Janeiro.

Imbert, C., Ulyssea, G., 2024. Rural Migrants and Urban Informality: Evidence from Brazil. Mimeo, University College London.

Jaeger, A, D., Ruist, J., Stuhler, J., 2019. Shift-share instruments and dynamic adjustments: the case of immigration. Mimeo.

Kleemans, M., Magruder, J., 2018. Labour Market Responses To Immigration: Evidence From Internal Migration Driven By Weather Shocks. Economic Journal 128 (613), 2032–2065.

Kovak, B. K., 2013. Regional effects of trade reform: What is the correct measure of liberalization? American Economic Review 103 (5), 1960–1976.

Kubik, Z., Maurel, M., 2016. Weather Shocks, Agricultural Production and Migration: Evidence from Tanzania. Journal of Development Studies 52 (5), 665–680.

Lewis, E., Peri, G., 2015. Immigration and the Economy of Cities and Regions. In: Handbook of Regional and Urban Economics, vol. 5A, 1st Edition. Vol. 5. Elsevier B.V., Ch. 10, pp. 625–685.

Llull, J., 2018. Immigration, wages, and education: A labour market equilibrium structural model. Review of Economic Studies 85 (3), 1852–1896.

Meghir, C., Narita, R., Robin, J.-M., 2015. Wages and informality in developing countries. American Economic Review 105 (4), 1509–1546.

Morten, M., Oliveira, J., 2023. The Effects of Roads on Trade and Migration: Evidence from a Planned Capital City. Forthcoming: American Economic Journal: Applied Economics.

Oliveira, J., Pereda, P., 2020. The impact of climate change on internal migration in Brazil. Journal of Environmental Economics and Management 103, 102340.

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

Peri, G., 2016. Immigrants, Productivity, and Labor Markets. Journal of Economic Perspectives 30 (4), 3–30.

Perry, G. E., Maloney, W. F., Arias, O. S., Fajnzylber, P., Mason, A. D., Saavedra-Chanduvi, J., 2007. Informality: Exit and Exclusion. The World Bank, Washington, DC.

Reis, E. J., Pimental, M., Alvarenga, A. I., 2007. Areas Minimas Comparaaveis para os Periodos Intercensitarios de 1872 a 2000.

Rozo, S. V., Sviatschi, M., 2021. Is a refugee crisis a housing crisis? Only if housing supply is unresponsive. Journal of Development Economics 148 (August 2020), 102563.

Stroebel, J., Vavra, J., 2019. House prices, local demand, and retail prices. Journal of Political Economy 127 (3), 1391–1436.

Ulyssea, G., 2018. Firms, Informality, and Development: Theory and Evidence from Brazil. American Economic Review 108 (8), 2015–2047.

UN-Habitat, 2004. The challenge of slums: Global report on human settlements 2003. Management of Environmental Quality: An International Journal 15 (3), 337—-338.

Vicente-Serrano, S. M., Beguería, S., López-Moreno, J. I., 2010. A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. Journal of Climate 23 (7), 1696–1718.

Appendix

Additional tables and figures

Appendix Table 1: Descriptive Statistics of Labor and Housing Markets Outcomes of Residents

	Base-year variables (1991)		Changes (1991-2010)	
	Mean	Std. dev.	Mean	Std. dev.
	(1)	(2)	(3)	(4)
Panel A: Labor-market Outcomes				
Mean Log Wages	6.20	0.31	0.38	0.18
Log Total Employment	9.99	1.18	0.52	0.27
Labor Force Participation Rate	0.60	0.06	0.06	0.06
Share of Employment in Services	0.55	0.14	0.10	0.08
Share of Employment in Manufacturing	0.15	0.11	-0.00	0.06
Share with high school or more	0.14	0.06	0.24	0.04
Informality Rate (including self-employment)	0.50	0.17	-0.04	0.07
Informality Rate	0.21	0.10	0.02	0.08
Panel B: Housing-market Outcomes				
All residents' housing units				
Mean Log Housing Rents	4.97	0.51	0.42	0.42
Log Total Number of Housing Units	9.64	1.16	0.59	0.23
Log Total Number of Rooms	11.35	1.17	0.64	0.26
Ownership Rate	0.68	0.08	0.05	0.10
Penurious housing				
Mean Log Housing Rents	4.79	0.78	0.37	0.79
Log Total Number of Housing Units	6.33	1.89	-0.64	0.87
Log Total Number of Rooms	7.59	1.95	-0.38	0.91
Low-quality housing				
Mean Log Housing Rents	4.96	0.55	0.45	0.48
Log Total Number of Housing Units	9.01	1.25	0.23	0.55
Log Total Number of Rooms	10.70	1.25	0.30	0.53
Quality housing				
Mean Log Housing Rents	4.99	0.55	0.44	0.50
Log Total Number of Housing Units	8.04	2.20	1.46	1.19
Log Total Number of Rooms	9.93	2.18	1.41	1.18

Notes: All values are cross-city averages of the corresponding variables. City aggregates are computed directly from the census microdata, restricted to observations of residents.

Appendix Table 2: Characteristics of Internal Migrants Who Arrived in Urban Areas in the 2000–2010 Period (national averages)

	Urban–urban	Rural–urban from moderate-weather origins	Rural–urban from severe-weather origins
Panel A: demographic characteristics			
Working-age rural–urban migrants (in 1000s)	6,570	3,840	155
Percent of females	50.8%	51.3%	51.3%
Age at the time of migrating			
Percent 15–30	55.3%	65.0%	65.2%
Percent 31 or older	44.7%	35.0%	34.8%
*Education**			
Percent less than primary	13.4%	20.5%	19.2%
Percent primary but less than high school	33.7%	41.3%	41.8%
Percent high school or higher	52.9%	38.2%	39.0%
Panel B: labor-market performance in destination cities in 2010			
Employment rate	64.9%	65.5%	62.9%
Difference from the urban average (pp.)	2.1	2.7	0.1
Informality rate	37.4%	37.5%	39.8%
Difference from the urban average (pp.)	-1.3	-1.2	1.2
Wages (in 2010 BRL)	1105	756	754
Relative to nonmigrant urban residents	123%	84%	84%
Panel C: housing conditions in destination cities in 2010			
Percentage of households that rent	49%	49%	49%
Difference from the urban average (pp.)	28.90	28.88	28.86
Rent (in 2010 BRL)	386	278	284
Relative to nonmigrant urban residents	125%	90%	92%
Relative to rural municipality of origin	214%	154%	158%

Notes: All values are national averages calculated from the microdata using sampling weights. All variables in Panel A refer to migrants' characteristics at the time of migration. Variables in Panel B are calculated for individuals that were of working age in the 2010 census. Informal workers are defined as those who are without a signed working card or are self-employed. Migrants from moderate-weather origins are defined as those coming from municipalities where the dryness measure was less than one standard deviation away from the historical average in the three years prior to migration. Migrants from severe-weather origins are those coming from municipalities with dryness more than one standard deviation away from the historical average in the three years prior to migration.

* To capture premigration educational attainment, these measures are calculated with the sample restricted to individuals aged 18 or older at the time of migration (that is, the age at which individuals are expected to have finished high school in Brazil).

Appendix Table 3: Effects of Weather-Induced Immigration on the Local Housing Market of Residents and Migrants, by Housing Quality

	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)
Panel A: All housing units				
Δ Mean Log Housing Rents	-0.014***	0.058***	0.050**	0.057***
	(0.004)	(0.022)	(0.020)	(0.022)
Δ Log Total Number of Housing Units	0.008***	0.005	0.011	0.011
	(0.001)	(0.011)	(0.007)	(0.008)
Δ Log Total Number of Rooms	0.006***	0.011	0.015*	0.017*
	(0.001)	(0.012)	(0.008)	(0.009)
Panel B: By housing quality				
Penurious housing				
Δ Mean Log Housing Rents	-0.014	0.027	-0.020	-0.002
	(0.016)	(0.052)	(0.043)	(0.053)
Δ Log Total Number of Housing Units	-0.016	0.179**	0.159**	0.180*
	(0.022)	(0.085)	(0.074)	(0.095)
Δ Log Total Number of Rooms	-0.016	0.198**	0.182**	0.212**
	(0.022)	(0.088)	(0.077)	(0.100)
Low-quality housing				
Δ Mean Log Housing Rents	-0.019***	0.069***	0.059**	0.064**
	(0.004)	(0.025)	(0.023)	(0.026)
Δ Log Total Number of Housing Units	-0.027***	-0.114***	-0.117***	-0.123***
	(0.006)	(0.039)	(0.034)	(0.040)
Δ Log Total Number of Rooms	-0.026***	-0.090**	-0.094***	-0.096***
	(0.005)	(0.037)	(0.032)	(0.036)
Quality housing				
Δ Mean Log Housing Rents	-0.018***	0.028	0.044	0.056
	(0.004)	(0.030)	(0.035)	(0.044)
Δ Log Total Number of Housing Units	-0.020	-0.161	-0.179	-0.218
	(0.013)	(0.105)	(0.115)	(0.144)
Δ Log Total Number of Rooms	-0.021	-0.158	-0.171	-0.207
	(0.013)	(0.105)	(0.113)	(0.142)
Macroregion fixed effects	Yes	Yes	Yes	Yes
Main controls set	Yes	No	Yes	Yes
Log population control	Yes	No	No	Yes

Notes: The table reports the results of city-level regressions. City aggregates are computed directly from the census microdata as averages across households. We define housing quality using a vector of four housing attributes that are consistently observable across censuses: sewage network, trash collection, brick walls, and water network. If a house is missing all four of these attributes, it is classified as penurious, and if it is missing at least one, low quality. Houses that are not missing any of these attributes are classified as quality housing. Due to data constraints, the number of observations varies by sub-sample, corresponding to 453, 195, 453, and 311 for all, penurious, low-quality, and quality housing units, respectively. The controls vector in column 2 includes employment shares in manufacturing, services, and government, the share of workers with college education, and population growth from 1980–1991. Exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in Appendix C (equation 5), are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Appendix Table 4: Effects of Weather-Induced Immigration on the Local Housing Market of Recent Migrants, by Housing Quality

	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)
Panel A: Penurious housing				
Δ Mean Log Housing Rents	0.037	0.027	-0.217	-0.746
	(0.028)	(0.245)	(0.441)	(1.999)
Δ Log Total Number of Housing Units	-0.147***	-0.186	-0.790	-2.198
	(0.051)	(0.370)	(1.091)	(5.941)
Δ Log Total Number of Rooms	-0.159***	-0.203	-0.758	-2.092
	(0.056)	(0.406)	(1.084)	(5.699)
Panel B: Low-quality housing				
Δ Mean Log Housing Rents	-0.021***	0.025	0.012	0.014
	(0.004)	(0.025)	(0.023)	(0.026)
Δ Log Total Number of Housing Units	-0.022***	-0.205***	-0.199***	-0.221***
	(0.007)	(0.065)	(0.056)	(0.068)
Δ Log Total Number of Rooms	-0.023***	-0.196***	-0.189***	-0.209***
	(0.007)	(0.063)	(0.054)	(0.065)
Panel C: Quality housing				
Δ Mean Log Housing Rents	-0.030***	0.076**	0.106**	0.134*
	(0.006)	(0.034)	(0.051)	(0.068)
Δ Log Total Number of Housing Units	0.017**	-0.064	-0.103	-0.132
	(0.008)	(0.071)	(0.099)	(0.131)
Δ Log Total Number of Rooms	0.014*	-0.096	-0.141	-0.176
	(0.008)	(0.077)	(0.108)	(0.143)
Macroregion fixed effects	Yes	Yes	Yes	Yes
Main controls set	Yes	No	Yes	Yes
Log population control	Yes	No	No	Yes

Notes: The table reports the results of city-level regressions. City aggregates are computed directly from the census microdata as averages across households, where the head of household is a recent migrant, defined as those that arrive in the city during the last five years prior to the census. We define housing quality using a vector of four housing attributes that are consistently observable across censuses: sewage network, trash collection, brick walls, and water network. If a house is missing all four of these attributes, it is classified as penurious, and if it is missing at least one, low quality. Houses that are not missing any of these attributes are classified as quality housing. Due to data constraints, the number of observations varies by sub-sample, corresponding to 59, 434, and 266 for penurious, low-quality, and quality housing units, respectively. The controls vector in column 2 includes employment shares in manufacturing, services, and government, the share of workers with college education, and population growth from 1980–1991. Exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in Appendix C (equation 5), are reported in parentheses. * p <0.1 , ** p < 0.05, and *** p < 0.01.

Appendix Table 5: Robustness Tests of Heterogeneous Effects of Weather-Induced Immigration on Labor Market Outcomes

	Baseline results (1)	Population growth control (2)	Commuting time control (3)	Clustered SE Mesoregion (4)	Absolute value of SPEI as instrument (5)	Lagged shocks control (6)
Panel A: By industry						
Services						
Δ Mean Log Wages	-0.075***	-0.089***	-0.075***	-0.075**	-0.159**	-0.073***
	(0.023)	(0.028)	(0.023)	(0.033)	(0.078)	(0.022)
Δ Log Total Employment	0.029**	0.026*	0.030**	0.029	0.016	0.028**
	(0.013)	(0.014)	(0.013)	(0.020)	(0.023)	(0.013)
Manufacturing						
Δ Mean Log Wages	-0.042**	-0.050**	-0.042**	-0.042	-0.052	-0.040**
	(0.017)	(0.022)	(0.017)	(0.026)	(0.041)	(0.016)
Δ Log Total Employment	0.149***	0.165***	0.150***	0.149***	0.263***	0.145***
	(0.031)	(0.043)	(0.031)	(0.041)	(0.096)	(0.030)
Panel B: By schooling attainment						
Less than high school						
Δ Mean Log Wages	-0.033*	-0.039*	-0.032*	-0.033	-0.070	-0.031*
	(0.017)	(0.021)	(0.017)	(0.027)	(0.046)	(0.016)
Δ Log Total Employment	-0.002	-0.009	-0.001	-0.002	-0.002	-0.002
	(0.011)	(0.011)	(0.011)	(0.017)	(0.020)	(0.011)
High school or more						
Δ Mean Log Wages	-0.087***	-0.104***	-0.087***	-0.087**	-0.181**	-0.085***
	(0.025)	(0.028)	(0.025)	(0.035)	(0.089)	(0.024)
Δ Log Total Employment	0.038**	0.034*	0.039**	0.038	0.010	0.033*
	(0.018)	(0.020)	(0.018)	(0.028)	(0.034)	(0.018)
Panel C: Among recent migrants						
Δ Mean Log Wages	-0.063***	-0.075***	-0.063***	-0.063*	-0.112*	-0.061***
	(0.021)	(0.027)	(0.021)	(0.033)	(0.061)	(0.020)
Δ Log Total Employment	-0.039	-0.069	-0.040	-0.039	-0.126	-0.038
	(0.040)	(0.042)	(0.041)	(0.056)	(0.106)	(0.040)
Macroregion fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Main controls set	Yes	Yes	Yes	Yes	Yes	Yes
Log population control	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the results of city-level regressions. All columns include macroregion fixed effects, the main controls set, and the logarithm of the 1991 population. Average commute time (column 3) is estimated based on midpoints of the time intervals available in the census. In column 5, the IV is constructed by interacting the absolute value of the SPEI (2000–2009) of each rural municipality of origin with the share of migrants from that municipality in total rural-urban migration to a city from 1982 to 1991. Column 6 adds the lagged shift-share instrument for the 1981-1990 period as a control. In all columns, exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in equation 5, are reported in parentheses, except for column 4, where they are clustered at the mesoregion level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Appendix Table 6: Robustness Tests of Heterogeneous Effects of Weather-Induced Immigration on Housing Market Outcomes

	Baseline results (1)	Population growth control (2)	Commuting time control (3)	Clustered SE Mesoregion (4)	Absolute value of SPEI as instrument (5)	Lagged shocks control (6)
Panel A: Penurious housing						
Δ Mean Log Housing Rents	-0.071	-0.133	-0.075	-0.071	-0.259	-0.076
	(0.063)	(0.109)	(0.064)	(0.072)	(0.315)	(0.065)
Δ Log Total Number of Housing Units	0.313***	0.499**	0.314***	0.313**	0.643	0.311***
	(0.106)	(0.220)	(0.106)	(0.144)	(0.667)	(0.107)
Δ Log Total Number of Rooms	0.339***	0.536**	0.340***	0.339**	0.598	0.334***
	(0.113)	(0.240)	(0.113)	(0.155)	(0.621)	(0.114)
Panel B: Low-quality housing						
Δ Mean Log Housing Rents	0.071***	0.079**	0.072***	0.071*	0.043	0.071***
	(0.026)	(0.034)	(0.027)	(0.041)	(0.054)	(0.026)
Δ Log Total Number of Housing Units	-0.080**	-0.105***	-0.079**	-0.080*	-0.295**	-0.084***
	(0.033)	(0.036)	(0.032)	(0.044)	(0.136)	(0.032)
Δ Log Total Number of Rooms	-0.057*	-0.076**	-0.056*	-0.057	-0.260**	-0.062**
	(0.031)	(0.033)	(0.031)	(0.041)	(0.125)	(0.030)
Panel C: Quality housing						
Δ Mean Log Housing Rents	0.050	0.057	0.051	0.050	0.086	0.057
	(0.036)	(0.066)	(0.035)	(0.046)	(0.062)	(0.035)
Δ Log Total Number of Housing Units	-0.173	-0.329	-0.173	-0.173	-0.083	-0.131
	(0.117)	(0.244)	(0.115)	(0.176)	(0.146)	(0.100)
Δ Log Total Number of Rooms	-0.168	-0.318	-0.166	-0.168	-0.076	-0.125
	(0.115)	(0.238)	(0.113)	(0.172)	(0.143)	(0.098)
Panel D: Among recent migrants						
Δ Mean Log Housing Rents	0.029	0.031	0.029	0.029	0.033	0.029
	(0.023)	(0.027)	(0.023)	(0.033)	(0.045)	(0.022)
Δ Log Total Number of Housing Units	-0.074*	-0.109**	-0.075*	-0.074	-0.171	-0.071*
	(0.041)	(0.044)	(0.041)	(0.054)	(0.118)	(0.040)
Δ Log Total Number of Rooms	-0.109**	-0.148***	-0.110**	-0.109*	-0.272*	-0.105**
	(0.047)	(0.053)	(0.047)	(0.063)	(0.158)	(0.046)
Macroregion fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Main controls set	Yes	Yes	Yes	Yes	Yes	Yes
Log population control	Yes	Yes	Yes	Yes	Yes	Yes

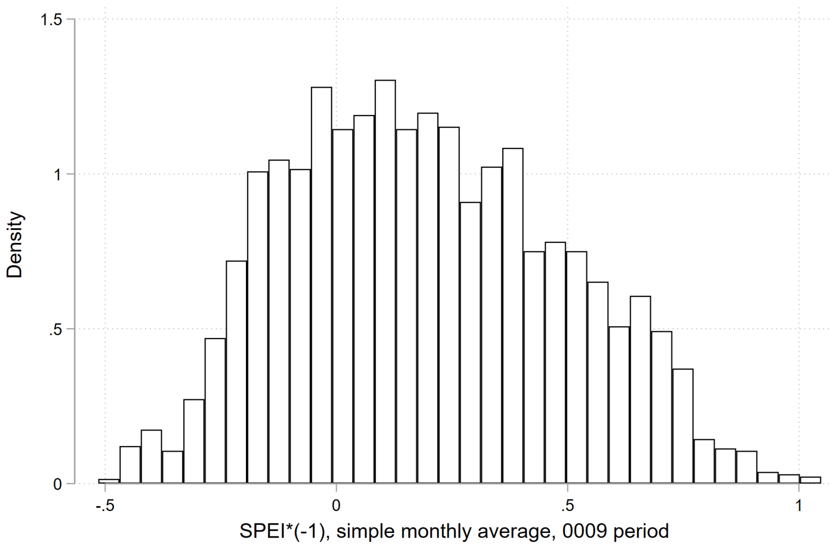
Notes: The table reports the results of city-level regressions. All columns include macroregion fixed effects, the main controls set, and the logarithm of the 1991 population. Average commute time (column 3) is estimated based on midpoints of the time intervals available in the census. In column 5, the IV is constructed by interacting the absolute value of the SPEI (2000–2009) of each rural municipality of origin with the share of migrants from that municipality in total rural-urban migration to a city from 1982 to 1991. Column 6 adds the lagged shift-share instrument for the 1981-1990 period as a control. In all columns, exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in equation 5, are reported in parentheses, except for column 4, where they are clustered at the mesoregion level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Appendix Table 7: Effects of Weather Shocks on Migration (using the absolute value of the SPEI measure)

	(1)	(2)	(3)
Panel A: Effects of precipitations on rural emigration			
	Emigration rate from rural areas		
Average Absolute Value SPEI	1.222***	1.043***	1.057***
	(0.274)	(0.267)	(0.266)
Observations	2,870	2,868	2,868
Average of dependent variable	8.527	8.520	8.520
Macrorregion fixed effects	Yes	Yes	Yes
Main controls set	No	Yes	Yes
Log population control	No	No	Yes
Panel B: Effect of weather-based IV on rural immigration			
	Rural immigration rate to cities		
SPEI-based shift-share IV	2.506***	2.573***	1.807**
	(0.943)	(0.847)	(0.819)
F statistic	7.06	9.23	4.86
Observations	454	454	454
Average of dependent variable	5.083	5.083	5.083
Macrorregion fixed effects	Yes	Yes	Yes
Main controls set	No	Yes	Yes
Log population control	No	No	Yes

Notes: The table reports the results of rural-municipality-level regressions (Panel A) and city-level regressions (Panel B), both calculated with data from the 2010 census. In Panel A, rural emigration is defined as the total number of emigrants who left a rural area in the 2001–10 period as a percentage of the 1991 population, and the drought index is the simple monthly SPEI (in absolute value) average for the 2000–2009 period. In Panel B, the endogenous independent variable (rural immigration rate) is defined as the number of rural migrants who arrived in a city during the same period as a share of the city's 1991 population. The IV is constructed by interacting the average of the absolute value of the SPEI measure (2000–2009) of each rural municipality of origin with the share that migrants from that origin represent in total rural-urban migration to a city from 1982 to 1991 (see equation 2). The vectors of controls in column 2 include the shares in employment of manufacturing, services, and government, the share of workers with college education, and 1980–91 population growth. Column 3 adds the log of 1991 population as control. In Panel A, robust standard errors clustered at the microregion level are reported in parenthesis. In Panel B, exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in equation 5, are reported instead. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Appendix Figure 1: Distribution of droughts measure (SPEI*-1)



Percentiles	
1%	-0.40
5%	-0.24
10%	-0.18
25%	-0.04
30%	-0.0000154
50%	0.17
75%	0.40
90%	0.61
95%	0.70
99%	0.86
Mean	0.19

Notes: The graph and table report the distribution of our dryness measure, defined as the monthly average of $-1 \times SPEI$ over the 2000–2009 period, of each rural municipality of origin.

A. Data appendix

A1. Variables Description

Appendix Table A1: Description of Measures

Variables	**Description/comments**
Working-age population	Population between 15 and 64 years old, inclusive
Employed	Individuals who answered being employed, regardless of formal registry status, in the census
Informal worker	People who answered not having formal work registry in a work card or declared being self-employed, in the census. This question is for individuals who answered being employed.
Severe-weather-driven rural migrant	Migrants who came from regions where the monthly drought-score average of the 36 preceding months prior to migrating is below -1 or above 1.
Moderate-weather-driven rural migrant	Migrants who came from regions where the monthly drought-score average of the 36 preceding months prior to migrating is between -1 and 1.
Resident	Individuals who lived in the reported place of residency for 10 years of more, or people who had not reported a previous place of residence.
Time-consistent urban areas	Similar to IBGE *arranjos*, time-consistent urban areas are urban conurbations that maintain the same boundaries for a selected period. In this study, all geographic unities are time consistent between 1980 and 2010.
Time-consistent rural areas	Non-*arranjo* municipalities, with municipal boundaries consistent between 1980 and 2010.
Rural migrant	Individuals whose previous location of residency was a rural time-consistent rural areas (up to 9 years before the census).

Appendix Table A2: Definitions of Variables

Variables	Description/comments
Panel A: Rural variables	
SPEI	Standardised Precipitation-Evapotranspiration Index developed by the Spanish National Research Council (Consejo Superior de Investigaciones Científicas). In this study, all SPEI scores were reversed (multiplied by -1). This was employed in order to represent positive values as droughts.
Rural emigration rate (2010-2001)	Total number of people who emigrated up to 9 years before the 2010 Census over the total rural population in the 1991 Census, per rural MCA.
Panel B: Urban variables	
Labor market outcomes	
Wages (adjusted by education and experience)	City-level average of the logarithm of the residuals of a national-level regression of wages on a vector of educational attainment indicators and a vector of age group. Wages are the monthly earnings in main occupation census, deflated to 2010 BRL values.
Employment	People who reported in the census as being employed, restricted by working age.
Housing market outcomes	
Housing rents (adjusted by unit characteristics)	City-level average of the logarithm of the residuals of a national-level regression of rents on a vector of dwelling characteristics including: log number of rooms, access to the main sewage system and trash collection service. Rents are the monthly housing rent reported in the census, deflated to 2010 BRL values.
Number of housing units (local stock)	Unique household observations in the Census
Number of rooms (local stock)	Sum of reported number of rooms in the Census, per unique household.
Controls	
Share of employment in large industries	Workers who reported working in four categories: agriculture, manufactures, services and government.
Share of college-educated in employment	Share of college educated in working age over all people employed in working age.
Population	Total respondants of the Census
Population growth 1980-1991	Difference of log of total population from 1991 Census and 1980 Census.

B. Labor Market Effects in the 2000-2010 Period

As discussed in Section 3.2 of the main text, data constraints only allow us to estimate housing market outcomes for the period 1991-2010, and to trace the origin of migrants—which we require to identify those from rural origins and measure our endogenous immigration variable—only for the period 2001-2010. Given these constraints, we measure all main outcomes as changes in local economies in the 1991-2010 period. For completeness, in this appendix, we estimate the effects of rural migration on urban labor market outcomes for the second decade of our study period (2000-2010), which matches the timeline in which the migration shock is measured.

Table B1 presents the results for labor market outcomes of residents measured as changes over the period 2000-2010. We find that, in this period, migration had a positive effect on both wages and employment (Panel A). A one-percentage-point increase in rural migration rates was associated with a 1.7 percent increase in wages and a 2.7 percent increase in total employment, relative to 2000 values.

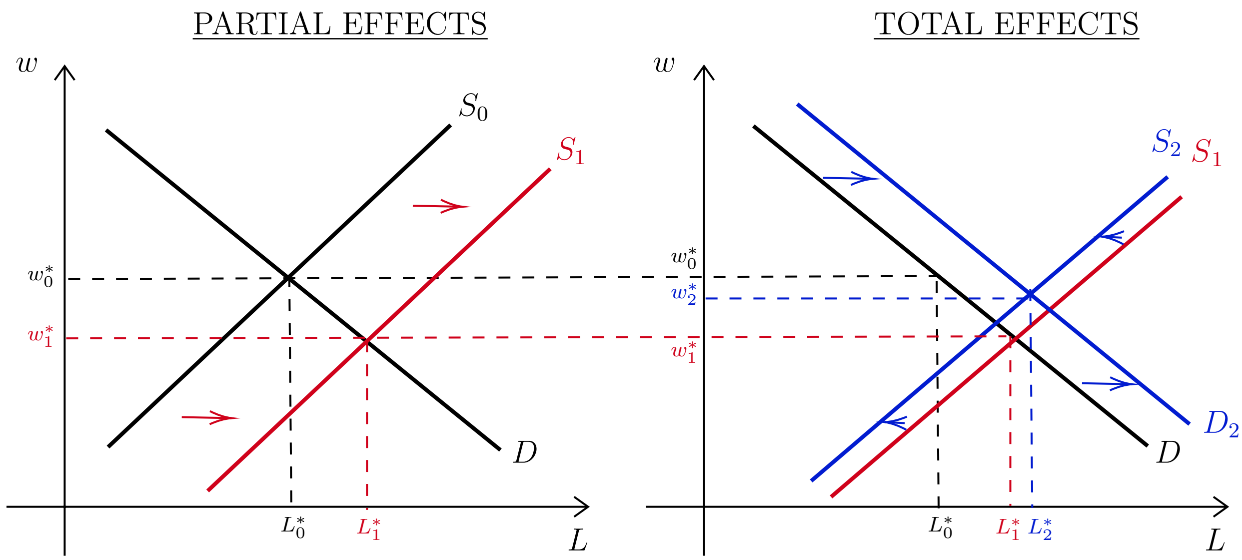
The differences between the effects measured relative to 1991 and those measured relative to the year 2000 are consistent with the theory discussed in Section 2.1, as well as with the labor market effects of migration beyond prices and quantities, discussed in Section 5.1. According to theory, if migrants' labor was a net substitute of resident labor, the migration-driven expansion in labor supply should have led to a negative effect on resident's wages and positive effect on employment, as illustrated in the left graph of Figure B1. These partial effects were then likely affected by other market adjustments. As documented in Section 5.1, residents responded to migration by moving to different cities, which would have mitigated the initial wage and employment effects by reducing labor supply. Migration also led to lower informality rates, which, as shown by Imbert and Ulyssea (2024), is explained by a higher entry of firms with high-growth potential that increases demand for both high-skilled and low-skilled workers, particularly in the formal sector. As illustrated in Figure B1 (right), the residents' supply contraction appears to have been smaller than the original supply growth and than the positive demand shift, such that the total equilibrium wage ended up being smaller than the baseline (measured in 1991) but larger if compared with the partial effect captured in the intermediate period, and the total employment effect was larger than both the baseline and the partial effect.

Appendix Table B1: Effects of Weather-Induced Immigration on Labor-market Outcomes of Residents

	OLS (1)	IV (2)	IV (3)	IV (4)
Panel A: All residents				
Δ Mean Log Wages	0.005***	0.014**	0.015***	0.017***
	(0.001)	(0.006)	(0.005)	(0.006)
Δ Log Total Employment	0.007***	0.020***	0.025***	0.027***
	(0.002)	(0.008)	(0.007)	(0.008)
Panel B: By industry				
Services				
Δ Mean Log Wages	0.003***	0.002	0.004	0.004
	(0.001)	(0.005)	(0.005)	(0.005)
Δ Log Total Employment	0.005***	0.028***	0.028***	0.031***
	(0.001)	(0.010)	(0.009)	(0.010)
Manufacturing				
Δ Mean Log Wages	0.008***	0.029***	0.029***	0.032***
	(0.002)	(0.011)	(0.009)	(0.011)
Δ Log Total Employment	0.021***	0.090***	0.085***	0.088***
	(0.005)	(0.018)	(0.018)	(0.021)
Panel C: By schooling attainment				
Less than high school				
Δ Mean Log Wages	0.007***	0.028***	0.029***	0.033***
	(0.002)	(0.008)	(0.007)	(0.008)
Δ Log Total Employment	0.009***	0.018**	0.020***	0.022***
	(0.001)	(0.007)	(0.006)	(0.007)
High school or more				
Δ Mean Log Wages	0.004***	-0.015**	-0.015**	-0.017**
	(0.001)	(0.008)	(0.007)	(0.008)
Δ Log Total Employment	-0.002	-0.015	-0.020	-0.023
	(0.002)	(0.018)	(0.014)	(0.015)
Panel D: Among recent migrants				
Δ Mean Log Wages	0.005*	0.030***	0.031***	0.034***
	(0.003)	(0.011)	(0.011)	(0.013)
Δ Log Total Employment	0.007	0.021	0.022	0.023
	(0.005)	(0.020)	(0.020)	(0.022)
Macroregion fixed effects	Yes	Yes	Yes	Yes
Main controls set	Yes	No	Yes	Yes
Log population control	Yes	No	No	Yes

Notes: The table reports the results of city-level regressions. The endogenous independent variable (rural immigration rate) is defined as the number of rural migrants who arrived in a city during the period between 2000 and 2010, as a share of the city's 1991 population. Dependent variables are the difference in the outcome of interest for residents in Panel A and Panel B, and for recent migrants in Panel C, within a given city between 2000 and 2010. In Panel D, recent migrants are defined as those that arrived in the city during the last five years prior to the census. For the wage measure we use the average of the residuals of an individual-level regression of the logarithm of the monthly wages on a vector of schooling attainment indicators and a vector of age categories indicators. Due to data constraints, the number of observations varies by sub-sample, with 454 for all outcomes except for Manufacturing, which has 453. The controls vector in column 2 includes employment shares in manufacturing, services, and government, the share of workers with college education, and population growth from 1980–1991. Exposure-robust standard errors (Borusyak et al., 2022) clustered at the microregion level, calculated as described in Appendix C (equation 5), are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Appendix Figure B1: Partial and Total Labor Market Effects of Migration



This interpretation requires us to assume the persistence of our exogenous variation across the two periods under study. We find support in the data for this assumption. Specifically, we construct alternative version of our 2000-2009 shift-share instrument, using the same shares component but relying on weather shocks from the 1991-1999 period instead. We find that the correlation between the 1990s shift-share and the 2000s shift-share is 25.85%, significant at the 99 percent confidence level.[24]

Turning to heterogeneity by industry (Panel B), we find that the effects in the 2000-2010 decade were more pronounced in manufacturing, with no effect on wages and smaller employment effects in the service industries. This is consistent with the interpretation that the demand effect of migration was relatively more pronounced in the manufacturing sector. In terms of schooling attainment (Table B1, Panel C), this decade's positive effects on wages were driven by resident workers with less that high-school education. Workers with high-school or higher education experienced a negative effect on wages and no statistically significant effects on employment over this period.

This is consistent with the fact that, as discussed in Section 5.1, residents responded to the partial effects of migration not only by moving to other cities, but also by increasing their educational attainment, implying that the labor supply contraction was relatively more pronounced among non-high-school workers. Lastly, Panel D of Table B1 looks at the effects

[24] In contrast, the correlation of the 2000s shift-share with the 1980s instrument (used in column 6 of our robustness Table (7) is of 3.82% (p-value=0.42).

on the outcomes of recent migrants, finding a positive effect on wages and no significant effects on employment, suggesting that both residents and migrants benefited from the labor demand effects of migration.

C. More on Shocks-Based Identification with Shift-Share Instruments

This appendix discusses more formally the identification assumptions and the estimation method employed in this paper, following the framework developed by Borusyak et al. (2022).

According to this framework, identification in our application relies on two assumptions. First, we assume conditional quasi-random assignment of the weather shocks. Formally, $\mathbb{E}\left[D_r|\bar{\varepsilon}, q, s\right] = q_r'\mu$, for all r, where $s = \{s_r\}_r$, $\bar{\varepsilon} = \{\bar{\varepsilon}_r\}_r$, $q = \{q_r\}_r$, and μ is the mean of the shocks D_r. Here, the conditioning variables are recast to the rural municipality level from the original city-level variables. Specifically, $s_r = \sum_c s_{c,r}$ are rural-municipality-level "exposure" weights (where exposure of a rural area to a destination city is measured as the share of that city in the total migration outflows from rural municipality r), $\bar{\varepsilon}_r = \frac{\sum_c s_{c,r}\varepsilon_c}{\sum_c s_{c,r}}$ is an exposure-weighted average of the unobserved destination-city residuals ε_c, and q_r is a vector of controls at the rural municipality level, which can be directly measured at that level or, as in our case, constructed as an exposure-weighted average of the correspondent city-level variables.

The second identifying assumption is that there are many uncorrelated shock residuals—such that a shock-level law of large numbers is applicable. Formally, we assume $\mathbb{E}\left[\sum_r s_r^2\right] \to 0$ and $Cov[\tilde{D}_r, \tilde{D}_{r'}|\bar{\varepsilon}, q, s] = 0$ for all (r, r') with $r' \neq r$.

A shift-share identification strategy that relies on shock-level exogeneity introduces potential complications in obtaining correct standard errors. Specifically, unobserved confounders at the shock level (in our case, at the level of rural municipalities) can result in dependencies between the shift-share instrument (Z_c) and the main regression's residual (ε_c) if multiple observations have similar exposure shares.

Borusyak et al. (2022) show that valid standard errors can be obtained by running a weighted IV regression at the shock level,[25] which in our application corresponds to:

[25] Adão et al. (2019) pioneered the study of this issue within the context of shift-share research designs, introducing a novel method to compute valid standard errors. In our work, we adopt the more recent solution put forth by Borusyak et al. (2022), which is not only more computationally efficient but also naturally follows

$$\overline{\Delta Y}_r^{\perp} = \delta + \beta \bar{I}_r^{\perp} + \bar{\varepsilon}_r^{\perp} \tag{5}$$

where superscript $\perp$ denotes the component of each variable that is orthogonal to the shock-level version of the vector of controls X_c, endogenous variable $\bar{I}_r$ is instrumented by the weather shocks at the rural municipality level (D_r), and regressions are weighted by shock-level exposure shares ($s_r = \sum_c s_{c,r}$). This regression yields numerically the same point estimates as the city-level regression in equation 1, but provide exposure-robust standard errors.

from their broader Econometric framework, which we have adopted in this paper.