Gender-Segmented Labor Markets and the Effects of Local Demand Shocks*

Juan Pablo Chauvin

Harvard University

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Abstract

Gender segmentation in the labor market is widespread. However, most existing studies of the effects of labor demand shocks on local economies assume away gender. In this paper, I show that local labor demand shocks can lead to different outcomes depending on whether they favor male or female employment. I develop a spatial equilibrium model that features gender segmented labor markets and joint mobility frictions, which predicts that couples are more likely to migrate in response to male opportunities. As a result, positive shocks to local labor demand for men lead to population growth, increases in female labor supply, and housing demand growth. Meanwhile, equivalent shocks to labor demand for women lead to smaller inflows of migrant workers, and labor force participation is a relatively more important margin of adjustment in this case. I find strong empirical support for the model's predictions in the context of Brazil during 1991-2010. Comparing the effects of gender-specific labor demand shocks, I show that male shocks produce a higher migratory response and make localities more populated and expensive. These results imply that place-making policies that create jobs for females are more likely to benefit residents while those that create male jobs are more likely to benefit immigrants and landlords.

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1. Introduction

For decades, researchers and policymakers have been interested in the question of how local economies react – in terms of wages, employment and real estate prices – to changes in labor demand. The answers to this question have shaped our understanding of the effectiveness and welfare consequences of local development policies (Moretti 2011). In this literature, researchers have typically assumed away gender differences in the labor market. However, gender differences exist, are large, and are likely to matter. Because male and females tend to segregate into different industries and occupations (Olivetti and Petrongolo 2014), labor demand can disproportionally favor men or women depending on which industries are growing faster. And because women are less likely than men to locate away from their families (Sorenson and Dahl 2016; Gemici 2011; Costa and Kahn 2000) and more likely to interrupt their careers at the time of marrying and having children (Goldin et al. 2017; Bertrand et al. 2010), increases in demand for male and female labor can have very different effects on migration and labor force participation. This paper incorporates gender into the analysis of labor demand shocks and studies how local economic outcomes respond depending on whether the new jobs favor male or female employment.

I first develop a framework to illustrate the theoretical mechanisms at play and generate predictions on the effects of gender-specific labor demand shocks. Specifically, I embed gender segmentation in the labor market and joint mobility frictions for couples in a standard spatial equilibrium model in the tradition of Rosen (1979) and Roback (1982). These modifications of the canonical framework yield an equilibrium in which local populations, employment, wages and housing rents can respond asymmetrically to equivalent shocks in male and and female labor demand.

My model assumes that male and female workers are employed in different industries, each producing an intermediate good, and each with its own productivity shifter subject to exogenous shocks. Intermediate goods are ultimately aggregated as imperfect substitutes to produce a final generic good. On the supply side, individuals have one unit of labor, which they allocate to the workforce if the wage is weakly larger than an exogenous cost of participating in the workforce. I assume that this cost is stochastic, and that the support of its distribution starts at a higher value for women than for men, reflecting extensive work that shows that women tend to face higher opportunity costs of labor force participation (Ponthieux and Meurs 2015).

All individuals are married and each female-male pair constitutes a household. Households choose locations to optimize their combined net wages, housing rents, and amenities; and migration arbitrages away household-level welfare differences across regions. The model predicts that, due to higher cost of participation, the contribution of females to household income will be smaller in expectation, and couples choosing a joint location will be more likely to migrate in response to male rather than female work opportunities.

A key insight of the model is that, because of these gender differences in migration elasticities, local labor and housing markets respond asymmetrically to equivalent shocks to male and female labor demand. If demand for male labor increases, it leads to local population growth and to shifts in female labor supply, as migrant male workers and their spouses move in. Housing demand increases with population, pushing housing rents and compensating differentials in wages up; while the relative abundance of female labor pushes their wages down. In contrast, shocks in the demand for female labor lead to smaller migration adjustments and effects on the housing and male labor markets, making labor force participation a relatively more important margin of adjustment in these cases.

In order to test the model's predictions I use data from Brazil during the 1991-2010 period. Using individual microdata from four editions of the population census I generate regional aggregates for 539 local labor markets with time-consistent boundaries. To measure exogenous shocks in gender-specific labor demand for each local labor market I introduce a variation of a well-known instrument proposed by Bartik (1991). My measure interacts national industry employment growth *for each gender* with local industry employment shares. It predicts what growth in a region's gender-specific employment would have been if the local industry shares had remained the same as in the starting year and if gender-specific employment had grown in local firms at the same rate as in same-industry firms in the rest of the country. I go beyond prior studies that use similar "shift-share" instruments assessing the plausibility of the identifying assumptions in the data, and adapting my empirical specifications to address potential identification concerns.

I find strong empirical support for the prediction that households migrate more in response to male than to female demand shocks. Male demand shocks increase the migrant population significantly more than female shocks. Joint mobility frictions seem to play an important role. Women migrate more in response to male demand shocks than to shifts in their own labor demand. The same is less true for men, whose migration responses to changes in female labor demand are much smaller. Consistent with these differential effects on population, I also find that male local demand shocks lead to growth in housing rents, and females shocks do not.

Turning to gender-specific labor market outcomes, I find that increases in male labor demand have a larger effect on own-gender employment and wages than equivalent changes in female labor demand. These differences are concentrated in the population without high-school education. In the context of the model, these findings suggests that male labor supply is more elastic than female labor supply – largely because of larger migration responses – and that nominal wages partly reflect compensating differentials for increases in the cost of living, which are larger after positive male shocks.

The effects of shocks to the other gender's local labor demand are generally consistent with the differential migration mechanism playing an important role, but also highlight the importance of other margins of adjustment. *Male shocks* increased the population of employed and of non-employed *females*, which is in line with the presence of male-led joint migration in which tied-migrant women find disproportionally less work opportunities. However, in spite of shifting female labor supply rightwards, male shocks had a positive – though marginally significant – effect on local female wages. This could be explained, in the context of the model, by large compensating differentials for housing rents increases. In practice, it could also be driven in by family income effects on female labor supply or by changes in the skills composition of female labor, which the framework does not consider.

In the aggregate, male demand shocks increased the employment and wage gender gaps both in the 1990s and the 2000s. Meanwhile, female demand shocks reduced the gender employment gap but not the wage gap. Together, the empirical results point to two important areas for future research: the household's labor force participation decisions and the interactions between gender and education in the context of joint migration across local labor markets.

The asymmetric response of male and female labor markets to demand shocks translates into asymmetric welfare effects. While male-leaning local demand shocks are more likely benefit immigrants and landlords, female-leaning shocks are more likely to favor incumbent residents. Higher demand for female workers implies higher employment for residents because firms tap proportionally more into a labor pool already present in the region. Moreover, the smaller immigration effect limits the pressure on local housing prices, and workers are likely to receive a larger fraction of the benefits than landlords (Moretti 2011). In contrast, because higher demand for male workers leads to a larger migratory response and increase in housing demand, migrant workers and landlords receive a larger share of the economic rents.

The results also have implications for regional development policies. Initiatives that seek to create jobs and boost growth in underdeveloped regions are very popular around the globe. My findings suggest that such policies can have very different effects depending on the gender composition of the jobs that are created, and on the initial levels of male and female employment. Benefits to local populations can quickly dissipate through migration and higher local costs of living if job creation favors men.

The contributions of this paper are relevant for several literatures. First, it relates to studies of the effects of labor demand shocks on local economic outcomes including Diamond (2016), Amior and Manning (2015), Bartik (2015), Beaudry et al. (2014), Notowidigdo (2013), Glaeser et al. (2005) and earlier work by Blanchard and Katz (1992), Bartik (1991) and Topel (1986). This literature either looks at outcomes for the labor force as a whole or by skill group, aggregating male and female workers, or restricting the analysis to males. Moreover, in these works the marginal migrant is assumed to be an individual. By introducing realistic yet tractable new assumptions – a joint location constraint for married couples, and a higher opportunity cost of participating in the labor force for females – my paper shows that local labor demand shocks of equivalent size can lead to very different population, rents, employment and wage outcomes depending on whether they favor male or female jobs.

This paper also contributes to the literature on the efficiency and welfare consequences of place-based policies including Kline and Moretti (2014a), Busso et al. (2013), Kline (2010) and Glaeser and Gottlieb (2008), among others;[1] and related work which focuses on the extent to which immigrants – as opposed to local residents – benefit from local demand shocks and has produced contradictory results (Partridge et al. 2009; Bartik 2004). My work shows that the gender composition of the shocks can play an important role in determining the workers-landlords and residents-immigrants splits of welfare effects.

A closely related series of studies looks at the effects of trade shocks on local economic outcomes (Dix-Carneiro and Kovak 2017; Acemoglu et al. 2016; Costa et al. 2016; Hakobyan and McLaren 2016; Carneiro and Kovak 2015; Autor et al. 2013; Kovak 2013; Edmonds et al. 2010; among others). Trade shocks are likely to have different effects in the labor demand for men and women because local exposure depends on the industry composition of places and industries differ in the gender composition of employment. In this context, my findings suggest that gender asymmetries in the labor market could help explain regional heterogeneity in the effects of changes in import competition and export demand.

Lastly, my work contributes to the literature on the the gender wage and employment gaps (Blau 2016; Goldin 2014; Bertrand et al. 2010; Goldin 2006; Albrecht et al. 2003; Blau and Kahn 2003, 2000; Altonji and Blank 1999; Galor and Weil 1996; Lazear and Rosen 1990; among many others)[2] by showing how they can be exacerbated by tied migration in the context of local labor and

[1]See Neumark and Simpson 2015 for a review.

[2]See Ponthieux and Meurs 2015 for a review.

housing markets. Male biases in labor demand, in addition to increasing the gender gap through higher male wages and employment, can also increase the relative abundance of female labor and push female wages downwards.

The remainder of the paper is organized as follows. Section 2 presents the model and discusses some of its predictions. Section 3 describes the data used in the analysis, presents relevant descriptive facts, and describes the identification strategy. Section 4 presents and discusses the empirical results. Section 5 discusses welfare and policy implications, and Section 6 concludes.

2. Spatial equilibrium with gender-segmented labor markets

In this section I develop a spatial equilibrium model that illustrates how labor demand shocks can affect employment, wages, population, and labor force participation for men and women. It incorporates the standard elements from the seminal Roback (1982) framework where local wages, housing rents, and amenities determine the geographic sorting of workers and the utility of the marginal migrant is equalized across space in equilibrium. This kind of model has been extensively used in urban economics to study the effects of local labor demand shocks in the U.S. and other high-income countries, but its use in less-developed countries has not been as extensive (see Alves 2016, Morten and Oliveira 2016, and Oliveira and Pereda 2015 for recent applications in the context of Brazil).[3] It has significant advantages relative to partial equilibrium approaches because it captures how aggregate labor outcomes are shaped both by the direct effects of the shock and by the endogenous adjustments of factors prices and quantities (Moretti 2011).

I depart from the standard model by incorporating segmentation by gender in the labor market and joint mobility constraints for married households.[4] In my model the population consists of N married households indexed i, each with two members, a woman (W) and a man (M). There are a total of J regions indexed by j. Years are indexed by t. Each individual is endowed with one unit of labor. On the demand side, male and female workers are employed in different industries, each producing an intermediate good. Intermediate goods are ultimately aggregated as imperfect substitutes to produce a nationally-traded good. Each industry has its own productivity shifter,

[3] In some cases the use of this framework may not be appropriate (Gollin et al., 2017). Chauvin et al. (2017) argue that in India, where geographic mobility is low and human capital heterogeneity extreme, a spatial equilibrium may not develop. However, the strong correlation between local wages and housing rents in Brazil and its higher internal mobility support the adequacy of the framework in this context.

[4] The notion that joint mobility constraints can partly explain gender differences in labor market outcomes has previously been previously explored by Gemici (2011) and Frank (1978) in the context of partial-equilibrium search models. To the best of my knowledge, this is the first paper to incorporate this constraint into a general spatial equilibrium framework.

which is subject to exogenous shocks.

Individuals who sort into paid work incur a labor force participation cost φ_i, which is an exogenous stochastic variable with distribution $F(\varphi_i)$. This cost may reflect commuting (Black et al. 2014), childcare (Baker et al. 2008; Paes de Barros et al. 2011), or household appliances (Greenwood et al. 2005), among others. A key assumption of my model is that the distribution of this cost is gender-specific, such that the support starts at a value that is higher for women than for men by T_t. This is meant to reflect extensive work documenting a higher opportunity costs of labor force participation for females (Ponthieux and Meurs 2015). In this paper I abstract from the specific mechanisms that may drive this difference, and focus on its local labor market consequences.[5]

Households observe local wages, housing rents and amenities, but they only learn their labor force participation costs after choosing a location. However, they know in advance $F(\varphi_i)$, and consequently their expected labor income net of participation costs in each region. After choosing a location, individuals decide whether to sort into the workplace or into domestic production by comparing wage income and the cost of participating in the labor force. For simplicity, I assume away unemployment in the model.

2.1. Production and labor demand

I assume that males and females sort into different industries, Y_G for $G = \{M, W\}$, where their labor is combined with traded capital K and non-traded capital $\bar{Z}_j$[6] to produce an intermediate good with the production function:[7]

$$Y_{Gjt} = \psi_{G_{jt}} N_{Gjt}^{\beta} K_{jt}^{\gamma} \bar{Z}_j^{\,1-\beta-\gamma}$$

Intermediate goods are combined with constant elasticity of substitution into a nationally-traded generic final good priced one, according to:

$$\begin{aligned} Y_{jt} &= \left(Y_{Wjt}^{\sigma} + Y_{Mjt}^{\sigma}\right)^{\frac{1}{\sigma}}, \text{ or} \\ Y_{jt} &= \left[\left(\psi_{W_{jt}} N_{Wjt}^{\beta}\right)^{\sigma} + \left(\psi_{M_{jt}} N_{Mjt}^{\beta}\right)^{\sigma}\right]^{\frac{1}{\sigma}} K_{jt}^{\gamma} \bar{Z}_j^{\,1-\beta-\gamma}. \end{aligned} \tag{1}$$

I assume that $0 \leq \sigma \leq 1$, which is equivalent to assuming that male and female effective labor are

[5]Similar simplifications can be found in Albanesi and Sahin (2017) and Garibaldi and Wasmer (2005).

[6]Non-traded capital is added to the production function so that there can be constant returns to scale at the firm level but decreasing returns to scale at the region level. Under these conditions it is possible to have a zero-profit condition for firms and a finite size of regions (Glaeser, 2008).

[7]I assume that regions have many homogeneous firms, so that the region-level production function is the same as the firm's. Individual firms' indexes are omitted for simplicity.

imperfectly substitutable factors of production with elasticity of substitution $\frac{1}{1-\sigma}$. This assumption is consistent with international empirical evidence (Olivetti and Petrongolo 2014; Johnson and Keane 2013; Acemoglu et al. 2004). Traded capital can be purchased in any amount at price one. The firms' problem is:

$$\max_{N_{Mjt},N_{Wjt},K_{jt}} \left\{ \left[\left(\psi_{W_{jt}} N_{Wjt}^{\beta} \right)^{\sigma} + \left(\psi_{M_{jt}} N_{Mjt}^{\beta} \right)^{\sigma} \right]^{\frac{1}{\sigma}} K_{jt}^{\gamma} \bar{Z}^{1-\beta-\gamma} - W_{Wjt}N_{Wjt} - W_{Mjt}N_{Mjt} - K_{jt} \right\}$$

The solution yields the labor demand equations:

$$\begin{aligned} W_{Gjt} &= \beta\gamma^{\frac{\gamma}{1-\gamma}} \psi_{Gjt}^{\sigma} N_{Gjt}^{\beta\sigma-1} L_{jt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}} \bar{Z}^{\frac{1-\beta-\gamma}{1-\gamma}} \\ L_{jt} &= \left[\left(\psi_{W_{jt}} N_{Wjt}^{\beta} \right)^{\sigma} + \left(\psi_{M_{jt}} N_{Mjt}^{\beta} \right)^{\sigma} \right]^{\frac{1}{\sigma}} \end{aligned} \tag{2}$$

This formulation provides insights about the effects of gender-specific productivity shocks on the local wage gap, which is given by:

$$\frac{W_{Mjt}}{W_{Wjt}} = \left(\frac{\psi_{Mjt}}{\psi_{Wjt}} \right)^{\sigma} \left(\frac{N_{Mjt}}{N_{Wjt}} \right)^{\beta\sigma-1} \tag{3}$$

Equation 3 shows that the local gender wage gap depends on the gender productivity difference, the degree of substitutability of male and female labor, and on the relative abundance of male and female workers. The *direct* effect of gender-specific shocks on the gap will be positive in the case of males ($\frac{\partial \left(W_{Mjt}/W_{Wjt} \right)}{\partial \psi_{Mjt}} > 0$), and negative in the case of females ($\frac{\partial \left(W_{Mjt}/W_{Wjt} \right)}{\partial \psi_{Wjt}} < 0$). However the *total* effect depends on how changes in male and female productivity affect the ratio of male to female workers. For example, if male productivity shocks generate larger migratory responses and make male labor relatively more abundant than female labor ($\frac{\partial \left(N_{Mjt}/N_{Wjt} \right)}{\partial \psi_{Mjt}} > 0$), they would also have a negative partial effect on the wage gap under the imperfect substitutes assumption ($0 \geq \sigma \geq 1$). Likewise, increases in female productivity could worsen the wage gap if female migration effects are large enough to topple the wage productivity premium.

2.2. Household utility

Households chose locations to optimize a joint Cobb-Douglas utility function. As is standard in spatial equilibrium models following Roback (1982), they collectively derive utility from the consumption of a composite tradable good C_{ijt} priced one, housing rented at R_{jt},[8] and a local amenities index θ_j, which I assume to be exogenous and time-invariant for simplicity.[9] The household optimization problem is thus given by:

$$\max_{C_{ijt},H_{ijt}} \left\{ \theta_j C_{ijt}^{1-\alpha} H_{ijt}^{\alpha} \right\} \ s.t. \ W_{ijt}^{net} = C_{ijt} + R_{ijt} H_{ijt}$$

where $W_{ijt}^{net} = W_{Mijt}^{net} + W_{Wijt}^{net}$ is the household-level net labor income, and

$$W_{Gjt}^{net} = \begin{cases} W_{Gjt} - \varphi_{it} & \text{if the person sorts into the workforce} \\ 0 & \text{if the person does not} \end{cases}$$

The optimized housing consumption is therefore:

$$H_{ijt}^{*} = \alpha \frac{W_{ijt}^{net}}{R_{jt}} \tag{4}$$

Substituting the budget constraint and the optimal housing consumption into the utility function, one can express indirect utility of household i living in region j at time t as:

$$V_{ijt}\left(\theta_j, W_{ijt}^{net}, R_{jt}\right) = \alpha^{\alpha} \left(1-\alpha\right)^{1-\alpha} \theta_j W_{ijt}^{net} R_{jt}^{-\alpha} \tag{5}$$

The spatial equilibrium assumption implies that the indirect utility is equalized across space for the marginal household, $V_{ijt}\left(\theta_j, W_{ijt}^{net}, R_{jt}\right) = \underline{\mathrm{U}}$. Note that restricting the choice to a single location entails that household utility may be smaller that in the standard spatial equilibrium framework, where individuals are able to chose location separately. If the individual spatial equilibrium utilities for men and women are $\underline{U}_M$ and $\underline{U}_W$, and the optimal combination of wages, rents and amenities are not in the same geographical region for both of them, then introducing a joint location constraint implies that at least one of the members of the household may reside in a sub-optimal location where $V_{Gijt} < \underline{U}_G$, implying $\underline{\mathrm{U}}_{ijt} \leq \underline{U}_M + \underline{U}_W$.

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[8]For simplicity, I do not include home production or leisure in this version of the the utility function. This helps to highlight the role gender-asymmetric migration responses in the model, at the cost of assuming away income effects. In a forthcoming extension of the model I introduce household production with positive utility value.

[9]An emerging literature has shown the importance of endogenous amenities in shaping local economic outcomes, including Albouy and Stuart (2017); Lee and Lin (2017); Diamond (2016); and Hanlon (2015). Because in my model couples choose a single location, endogenous amenities are unlikely to be a first-order determinant of differential responses of male and female labor markets to demand shocks. They could however, affect the gender welfare gap if male and female workers differ in their preferences over amenities.

2.3. Labor force participation

Individuals have a exogenous and stochastic labor force participation cost, which they draw after moving to a new region from a power law with CDF $F(\varphi_i) = \left(\frac{\varphi_i}{\varphi_{min}}\right)^{\iota}$, $\iota \in [0,1]$ and support $\varphi_i \in (1, \varphi_{max})$ for men and $\varphi_i \in (1+T_t, \varphi_{max})$ for women. Individuals sort into the workplace if their wage is weakly greater than their participation cost. This implies that the participation costs that make men and women indifferent are $\varphi^*_{Gjt} = W_{Gjt}$. The female labor supply is therefore given by $N_{Wjt} = N_{jt}\left(\frac{W_{Wjt}}{1+T_t}\right)^{\iota}$. The implied inverse labor supply function is:

$$W_{Wjt} = (1+T_t)\left(\frac{N_{Wjt}}{N_{jt}}\right)^{\frac{1}{\iota}} \tag{6}$$

Conversely, male labor supply is $N_{Mjt} = N_{jt}W^{\iota}_{Mjt}$, which corresponds to the inverse supply function:

$$W_{Mjt} = \left(\frac{N_{Mjt}}{N_{jt}}\right)^{\frac{1}{\iota}} \tag{7}$$

2.4. The housing market

Housing belongs to absentee landlords, who buy it from developers and rent it to local residents at R_{jt}. Profits for developers, are given by:

$$\pi_{jt} = \sum_{t=0}^{\infty} \frac{R_{jt}}{(1+r_t)^t} - CC_{jt}$$

where r_t is the national interest rate, and CC_{jt} are the local construction costs.[10]

There is free entry and the zero-profit condition holds, so that developers sell housing at the cost of construction, $\frac{(1+r_t)}{r_t}R_t = CC_{jt}$. For a given construction cost, there is a supply of $\bar{H} \cdot CC^{\rho}_{jt}$ units of housing, that is, additional units can be provided at higher construction costs with elasticity ρ. This implies that the local housing supply is given by:

$$\bar{H}\left(\frac{1+r_t}{r_t}\right)^{\rho} R^{\rho}_{jt} \tag{8}$$

Local housing demand is the aggregate from all N_{jt} households locating in region j at time t.

[10]The housing supply component of my model follows closely Glaeser (2008).

Based on equation 4, it can be written as:

$$\begin{aligned} H_{jt} &= \alpha \frac{\bar{W}_{jt}^{net}}{R_{jt}} N_{jt} \\ \bar{W}_{jt}^{net} &= \left(\frac{N_{Mjt}}{N_{jt}} W_{Mjt} - \bar{\varphi}_{Mjt} \right) + \left(\frac{N_{Wjt}}{N_{jt}} W_{Wjt} - \bar{\varphi}_{Wjt} \right) \end{aligned}$$

and $\bar{\varphi}_{Gjt}$ is the average participation cost for individuals of gender $G = \{M, W\}$ that sort into the workforce in region j.

In equilibrium demand and supply for housing equate, yielding the rent equation:

$$R_{jt}^{*} = \left(\alpha \frac{\bar{W}_{jt}^{net}}{\bar{H} \left(\frac{1+r_t}{r_t} \right)^{\rho}} N_{jt} \right)^{\frac{1}{1+\rho}} \tag{9}$$

2.5. Key insights and predictions

In this section, I describe the key insights and predictions provided by the model's analytical solution. Appendix C describes how I close the model, and gives greater detail about the resulting expressions.

Equation 9 allows me to re-write the indirect utility of households living in region j (equation 5) only in terms of the expected net household wage, local amenity levels, the city population and exogenous parameters. The net household wage enters the utility function as an expectation because, before migration, there is uncertainty about the individuals' participation costs. Under the spatial equilibrium assumption utility is equalized for the marginal migrant household making them indifferent with across locations, $V_{jt}\left(\theta_j, E\left(W_{jt}^{net}\right), N_{jt}\right) = \underline{U}$. The spatial indifference curve can be used to express the local population in terms of the expected net household wage:

$$N_j = \left[E\left(W_{jt}^{net} \right) \right]^{\frac{1+\rho-\alpha}{\alpha}} \left(\frac{\zeta \theta_j}{\underline{\mathrm{U}}} \right)^{\frac{1+\rho}{\alpha}} \tag{10}$$

where $\zeta := \frac{\alpha}{\bar{H}\left(\frac{1+r_t}{r_t}\right)^{\rho}}$ and $E\left(W_{jt}^{net}\right) = E\left(W_{Mjt}^{net}\right) + E\left(W_{Wjt}^{net}\right)$. In turn, the gender-specific expected net wage is given by:

$$\begin{aligned} E\left(W_{Wj}^{net}\right) &= \left(\frac{W_{Wjt}}{1+T_t} \right)^{\iota} \left[W_{Wjt} - \frac{\iota (1+T_t)}{\iota+1} \left(\left(\frac{W_{Wjt}}{1+T_t} \right)^{\iota+1} - 1 \right) \right] & (11) \\ E\left(W_{Mj}^{net}\right) &= W_{Mjt}^{\iota} \left[W_{Mjt} - \frac{\iota}{\iota+1} \left(W_{Mjt}^{\iota+1} - 1 \right) \right] & (12) \end{aligned}$$

where the probabilities of participating and the expected costs of participation for each gender follow from the functional form assumption on $F(\varphi_i)$ (see model solutions in Appendix C for details).

Relative effects of male and female demand shocks on population and rents

I am interested in comparing the effects of equivalent shocks to the productivity to the female-intensive industry ($\Delta\psi_{Wjt}$) and the male-intensive industry ($\Delta\psi_{Wjt}$) in region j, which correspond to shifts in female and male local labor demand respectively. From the labor demand equation 2 it is apparent that the partial effect on gender-specific wages is positive ($\partial W_{Gjt}/\partial\psi_{Gjt} > 0$) and its size is mediated by the elasticity of substitution of male and female labor (captured by σ).

The effects of gender-specific demand shocks on migration and ultimately population will in turn depend on how migrants react to changes in the expected male and female wage. Equation 11 shows that, in expectation, the contribution of the female wage to the household labor income is penalized by their incremental cost of participating in the labor force, T_t. The same is not true for the expected male wage in equation 12. It follows that demand shocks that affect the wages for males will have a larger impact on population – through migratory adjustments – than equivalent shocks affecting female wages.

Because a larger population increases housing demand and pushes the equilibrium rent up (see equation 9), shocks to labor demand for males – compared to equivalent shocks for female labor – will also have a larger effect on housing rents.

Effects of male and female shocks on employment

The equilibrium under autarky, which treats the regions' population as exogenous, is useful to provide intuition of the predictions of the model and the role played by migrant households constrained to choosing a single location. In the absence of migratory adjustments, the equilibrium female and male employment in region j are given respectively by:

$$N^{*aut}_{Wjt} = N_{jt}^{\frac{1}{1-\iota\xi_1}} \left(\frac{\lambda_1}{1+T_t}\right)^{\frac{\iota}{1-\iota\xi_1}} \psi_{Wjt}^{\frac{\iota\sigma}{1-\iota\xi_1}} \Psi_{Wjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}\frac{\iota}{1-\iota\xi_1}} \tag{13}$$

$$\Psi_{Wjt} = \left[\psi^{\sigma}_{W_{jt}} + \psi^{\sigma}_{M_{jt}}\left[(1+T_t)\left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\sigma}\right]^{\frac{\beta\iota\sigma}{1-\iota(\beta\sigma-1)}}\right]^{\frac{1}{\sigma}}, \text{ and}$$

$$
\begin{aligned}
N^{*aut}_{Mjt} &= N_{jt}^{\frac{1}{1-\iota\xi_1}} \lambda_1^{\frac{\iota}{1-\iota\xi_1}} \psi_{Mjt}^{\frac{\iota\sigma}{1-\iota\xi_1}} \Psi_{Mjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}\frac{\iota}{1-\iota\xi_1}} \\
\Psi_{Mjt} &= \left[\psi^{\sigma}_{W_{jt}} \left[(1+T_t)\left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\sigma}\right]^{\frac{\beta\iota\sigma}{\iota(\beta\sigma-1)-1}} + \psi^{\sigma}_{M_{jt}}\right]^{\frac{1}{\sigma}}
\end{aligned}
\tag{14}
$$

with constants $\lambda_1 := \beta\gamma^{\frac{\gamma}{1-\gamma}} \bar{Z}^{\frac{1-\beta-\gamma}{1-\gamma}}$, and $\xi_1 := \frac{\beta\gamma(1-\sigma)+(1-\gamma)(\beta\sigma-1)}{(1-\gamma)}$ (see Appendix C for details).

These equations show that the direct effect of shocks to own-gender labor demand on employment are positive for both men and women. The gender-specific industry productivity terms ψ_{Gjt} in equations 13 and 14 increase employment directly ($\frac{\iota\sigma}{1-\iota\xi_1} > 0$) and dominate the substitution effect captured by the term Ψ_{Gjt} (that is, $\partial\Psi_{Gjt}/\partial\psi_{Gjt} > 0$). The effect, however, is larger for the case of males than females, reflecting the latter's larger labor force participation costs. While $1 + T_t$ effectively scales down the constant λ_1 in equation 13, it does not have a similar effect in equation 14.[11] The larger employment effects of male shocks on own-employment are exacerbated in the open-region equilibrium, where population is endogenous. This is because, as discussed earlier, the own-gender migration effect is larger for men than for women. However, increases in housing rents acts as a counterbalancing force, deterring migration more in the case of male than of female shocks.

The effects of other-gender labor demand shocks on employment are also positive. In the absence of migration, this is driven primarily by the input substitution effect captured in Ψ_{Gjt}, and they are symmetric for both genders. With migration, however, an asymmetry arises. Male shocks have a disproportionally larger effect on female employment because of its larger effect on population N_{jt}.

Effects of male and female shocks on wages

In the autarkic equilibrium equilibrium female and male wages are given by:

$$
W^{*aut}_{Wjt} = N_{jt}^{\frac{\xi_1}{(1-\iota\xi_1)}} \left(\frac{\lambda_1}{1+T_t}\right)^{\frac{1}{1-\iota\xi_1}} \psi_{Wjt}^{\frac{\sigma}{1-\iota\xi_1}} \Psi_{Wjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}\frac{1}{1-\iota\xi_1}} \tag{15}
$$

$$
W^{*aut}_{Mjt} = N_{jt}^{\frac{\xi_1}{(1-\iota\xi_1)}} \lambda_1^{\frac{1}{1-\iota\xi_1}} \psi_{Mjt}^{\frac{\sigma}{1-\iota\xi_1}} \Psi_{Mjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}\frac{1}{1-\iota\xi_1}} \tag{16}
$$

Without household migration, the direct effect of shocks to own-gender labor demand on wages are positive for both genders and smaller for women. They enter the equation in the same structure as they do as in the employment equation, although the relative role of the input substitution

[11] The term $1 + T_t$ also enters the input substitution terms Ψ_{Gjt}, but its effect on the male and the female case is symmetrical.

term is larger.[12] The population term, however, enters the equations negatively ($\xi_1 < 0$). If the region is open to migration, the inflow of immigrants shifts the labor supply rightwards pushing wages down, but the effect is mitigated by the subsequent increase in housing rents, which deters further migration and induces firms to pay a compensating differential if they want to attract more labor. In the open region the effects on own-gender wages can be smaller for men than for women if the downward effect coming from migration, which favors female wages, dominates the differential penalty for participation costs T_t and the wage compensation for higher costs of living, which favor male wages. The net prediction on the effects of demand shocks on own-gender wages in ambiguous.

In the absence of migration, the effects on wages of other-gender labor demand shocks are also positive and symmetric for both genders, and are driven entirely by input substitution. Migration introduces a negative effect of other-gender shocks because population enters the equation negatively and couples move together. And because migration responds more to male shocks, the net effect of these shocks on female wages can be negative, unless the compensating differentials for higher housing rents are high.

In sum, the model delivers clear predictions on the effects of gender-specific demand shocks on local population, housing rents, and gender-specific employment; which are all positive and larger for male than for female shocks. The predictions of the model are ambiguous with respect to wages, and because of the role of wages in the decision to sort into the workforce (equations 6 and 7), they are also ambiguous with respect to participation rates. With this framework in mind, I turn now to the empirics.

3. Data, Facts and Identification Strategy

In this section, I describe the data and characterize a few features of Brazilian local labor markets over the period of interest to provide context for the analysis. I also present the identification strategy, discuss its key assumptions, and address potential identification concerns.

3.1. Data

The data used in this analysis comes primarily from the decennial population censuses of 1980 through 2010. The Brazilian Institute for Geography and Statistics (IBGE) makes available to researchers the microdata for the long-form questionnaire sample, which corresponds to 10% of the population in 1980 and 5% in the subsequent census years. I complement this with data from

[12]The direct effect has a smaller exponent given that $\sigma > \iota\sigma$, and the input substitution component a larger exponent given that $1 > \iota$.

other sources, including municipality areas and climate data from the Brazilian Institute of Applied Economic Research (IPEA), and GIS data from IBGE. Details of the sources and definition of the variables used in the analysis are included in the Data Appendix D. Appendix tables A.1 and A.2 present summary statistics of the main regional variables for the 1990s and the 2000s, respectively, and appendix tables A.3 and A.4 report correlations among these variables.

The definition of local labor markets used in the main specifications of the analysis is a Brazilian "microregion". Microregions are defined by the IBGE as groupings of contiguous and economically integrated municipalities (IBGE 2002), and a growing literature acknowledges them as good approximations of the boundaries of local labor markets, and uses them in regional research (Costa et al. 2016; Dix-carneiro and Kovak 2016; Adão 2015; Kovak 2013).

In order to be able to compare microregions across time, it is necessary to adjust for the changes in administrative boundaries. The number of Brazilian municipalities grew dramatically over this period, going from 3,992 in 1980 to 4,491 in 1991 and to 5,565 in 2010. In a number of cases the parents of newly-created municipalities belonged to different microregions. I create time-consistent boundaries by aggregating the original the IBGE microregions that share the same family tree over this period, as in Kovak (2013). The resulting sample includes 539 regions.[13] I use the microdata to generate regional-level aggregate measures for the different subsamples of interest (see Appendix D).

3.2. Descriptive facts

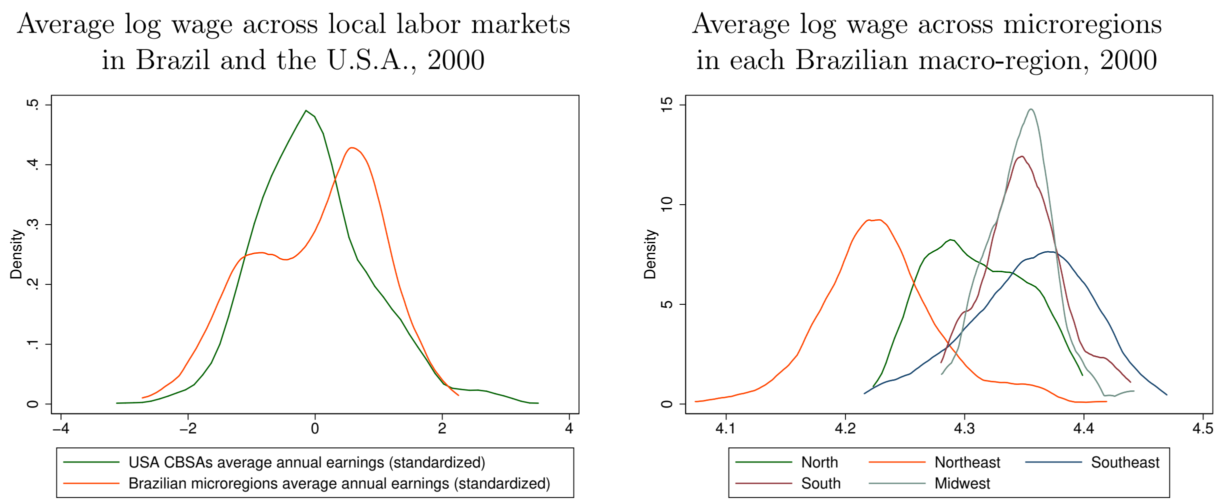
Brazil has been for many years among the countries with the highest economic inequality in the world. In 1991, the income share held by the top decile was 48.1%, much higher than in other large economies like India (26%), China (25.3%) or the US (26.7%) (Chauvin et al. 2017).

These disparities have major geographic and gender components. Economic opportunities are very unequally distributed over the national territory, especially across the poorer North and North East regions, and the richer South and South East regions. Figure 1 provides a stark illustration. The left panel contrasts the distribution of average labor income across Brazilian microregions with the same distribution across metropolitan statistical areas in the U.S.A. in the year 2000. While

[13]The number or time-consistent microregions is significantly larger than that generated by Kovak (2013). This is because this paper uses as an input time-consistent municipalities (a.k.a. "Minimum Comparable Areas" – MCAs) originally produced by Reis et al. (2007). In this database MCAs are more aggregated than needed for accurate comparisons over the period of interest. I first re-create MCAs using the official municipalities' family trees made available by the IBGE, and then generate time-consistent microregions using the new MCAs as input (see Data Appendix D). My empirical results are largely unchanged when I use the time-consistent microregions from Kovak (2013) to assess robustness, but in that case they are measured with less precision than in my main sample.

the average income of local labor markets in the U.S. follows a unimodal distribution, in Brazil the distribution is bi-modal. The left panel shows that, underlying this unconventional shape, are large differences in labor income among the main geographies of the country.

Figure 1: Distribution of labor income across local labor markets in Brazil and the U.S.A.



Inequality has also an important gender component, including a large gender wage gap and differences in labor force participation, work experience, and other correlates of labor productivity across men and women (Foguel 2016). Part of these differences are explained by the fact that, historically, females had less access to formal education. Appendix table A.5 shows that in 1991 the fraction of the population not participating in the labor force was twice as large in the sample with less than high-school education than in the sample with high-school or or higher education diploma. But even among the group with more formal education, non-participation rates were much higher for women (31%) than for men (7%) at the beginning of the decade.

Gender and geographic dimensions of inequality appear to be closely intertwined. In the cross section, the participation gender gap is more acute at lower income levels. Appendix Figure A.6 shows the distribution of labor force participation across local labor markets for the five Brazilian macro-region by gender and education group.[14] Local labor markets in poorer areas tend to have lower participation rates than in richer areas. This geographic differences are significantly less pronounced among the population with high-school education.

The country had very different macroeconomic performance across the two decades covered in this study. While 1990-2000 was a period characterized by volatility and rising unemployment, 2000

[14]Macroregions are the coarser statistical division in the country, roughly equivalent to U.S. census regions.

to 2010 were years of consistent growth and improving economic opportunities, particularly for the lower-income population. The 1990s started with a sharp reduction of trade barriers and a major push for the privatization of state-own enterprises. Hyperinflation, which had severely threatened the livelihood of millions of Brazilians during the 1980s and the early 1990s, was brought to a halt in 1994 by a series of economic measures known as the "Plano Real", and a fairly stable period ensued during the second part of the decade. This stability, however, was not enough to prevent a massive jobs loss, and by the end of the decade unemployment had increased by 11 percentage points relative to 1991 levels (Table A.5). In contrast, the 2000s saw important GDP and employment growth, accompanied by progress in inequality reduction, which was driven both by a compression in the distribution of labor income, and by the expansion of transfers to low-income families (De Barros et al. 2006).

The sharp differences between these two decades can be seen in Figure 2, which shows the national employment growth by industry and gender over these two periods. There were only a handful of industries that did not see net job loss during the 1990s. Employment was lost in primary industries, manufacturing and services. Job loss did not systematically hurt men or women across industries: while sectors like agriculture, textiles manufacturing and financial services saw a disproportionate loss in male employment, female employment was more affected in other sectors like mineral mining, rubber product manufacturing and utilities.

During the 2000s, in contrasts, most industries grew. Females saw a larger proportional growth in most industries, reflecting in part lower starting employment levels. But the relative growth of male and female jobs was heterogeneous across industries. My empirical strategy leverages these national gender differences to measure changes in male and female labor demand that are plausibly exogenous at the local level.

The increasing economic opportunities and shrinking inequality in the 2000s brought along a reduction of internal migration. In the 2000 census 17.41% of the population had been living in a different microregion ten years before. That number came down to 10.35% in the 2010 census. This reduction was driven by the subpopulation with lower levels of education (see Table A.6 for more on internal mobility). In terms of the framework presented in Section 2, this implies that asymmetric migratory responses to male and female demand shocks are likely to have played a less important role in determining local labor market outcomes in the 2000s than in the prior decade.

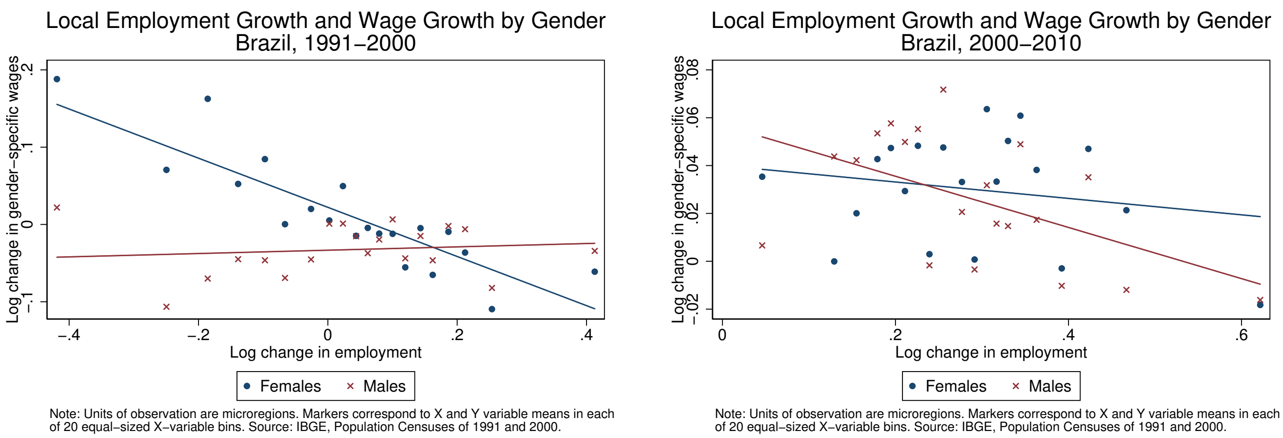
Figure 2: Employment growth by industry and gender, Brazil 1991-2010

Source: Own calculations using census data

Differences in the relative role of migration may help us understand the correlation of gender wage gap and local employment growth in different points in time. The bin scatter plots in Figure 3 measure total employment growth (including males and females) on the horizontal axis, and gender-specific wage growth on the vertical axis. The left panel shows that in the 1990s the relationship between employment and wage growth varied significantly by gender. While Brazilian microregions that experienced employment growth also saw shrinking female wages in this decade, places that lost employment witnessed increases in wages for women. The same was not true for the relationship between the male wage and employment growth, which had a weak, positive correlation in that decade. In contrast, in the 2000s both male and female local wages decreased as employment raised. The slope of the regression line was larger for men, but the fit was much weaker than in the prior decade for both genders.

Figure 3: Changes in Employment and the Gender Wage Gap

1990s **2000s**



For the demand-side of the market to explain a pattern like the one observed in the 1990s one would have to assume that the production technology is such that the relative demand for female labor drops in good times and increases in bad times. This would be consistent with the observed changes in female wages, but would fail to account for the relatively constant male wages. Moreover, it would not explain why the pattern changed in the following decade. The model presented in section 2 provides a potential supply-side explanation. If couples chose a single location and they are more responsive to male than to female job prospects, and if booms and busts in labor demand disproportionally affect men, migratory adjustments could account for the observed differences in wage growth in the 1990s. In turn, population growth and larger labor force participation of males could account for the patterns observed in the 2000s, when the migration margin was relatively less important.

3.3. Identification strategy

In this section I discuss the approach I use to empirically identify the effects of gender-specific changes in local labor demand on the labor and housing markets. Specifically, I am interested in measuring how migration, male and female wages and employment, and housing rents react to gender-specific labor demand shocks. The reduced-form relationship of interest for each of these outcomes is:

$$\Delta_{t-t_o} Outcome_j = \alpha + \beta_G \, \Delta_{t-t_o} Labor\, Demand_{jG} + \delta \, Controls_{j,t_0} + \Delta_{t-t_o} \epsilon_{jG} \tag{17}$$

where Δ_{t-t_o} denotes the log-change between the start year (t_0) and the end year (t) in region j; subscript G denotes gender (M or W); and ϵ_{jG} is the error term.

Gender-specific Bartik shocks

In order to estimate the effect of changes in labor demand I need a measure of demand shifts that is independent from local labor supply characteristics. I introduce a variant of "shift-share" shocks, widely used in the literature studying local economies following Bartik (1991). I construct gender-specific Bartik shocks interacting the aggregate industry employment growth for each gender with each region's start-year industry mix. Similar variations have been used in recent studies to instrument for changes in local female wages (Bertrand et al. 2015; Aizer 2010). Specifically, I calculate:

$$Bartik^G_{jt} = \sum_{ind} \underbrace{\eta_{ind,j,t_0}}_{\substack{\text{Local industry} \\ \text{shares at } t_0}} \underbrace{\left(\log N^G_{ind,-j,t} - \log N^G_{ind,-j,t_0}\right)}_{\substack{\text{National change in gender } G \\ \text{industry employment}}} \tag{18}$$

where $N^G_{ind,-j,t}$ is the number of workers of subgroup $G = \{M, W\}$ employed in industry ind at time t nationally, excluding region j; and η_{ind,j,t_0} is the share of employment of region j in industry ind at the start period (t_0). I use leave-one-out national employment growth, following Autor and Duggan (2003), to address concerns that the introduction of own-region employment may mechanically increase the predictive power of the shock. The gender-specific Bartik shocks in equation 18 predict what growth in a region's female (or male) employment would have been if the local industry shares had remained the same as in the starting year and gender-specific employment had grown in local firms at the same rate as in same-industry firms in the rest of the country. Appendix figure A.1 shows the distributions of male and female Bartik shocks for the two decades, and figure A.2 depicts the geographic distribution of these shocks.

Identifying assumptions

In spite of the widespread use of Bartik-style shocks, there was until recently little discussion on the ultimate source of the identifying variation. The standard identifying assumption is generally understood: conditional on controls, the shock should be uncorrelated with the error term ($\Delta_{t-t_o}\epsilon_{jG}$ in this context). However, the shock itself has two structural components, the local industry shares and the national industry growth rates, and it is a priori unclear which of them drives the exogenous variation.

Goldsmith-Pinkham et al. (2017) study this question, and conclude that identification in Bartik-style shocks comes exclusively from the local industry shares $\eta_{ind,j}$, while the national industry growth contributes only to predictive power. They show that using Bartik shocks in 2SLS estimation is numerically equivalent to using a GMM estimator where the weight matrix is constructed with the national growth rates, and the local industry shares alone are used as the instrument.[15]

This implies that the underlying identifying assumption for the shock in equation 18 to produce causal estimates is that the vector of industry shares is uncorrelated with the decade-long changes in error term conditional on the set of controls. In the same study, the authors assess this assumption in the data in the context of existing studies that use Bartik shocks to recover the shape of the local labor supply curve. They show that local industry shares are typically correlated with observable characteristics of a place, particularly measures of education, and that estimates that do not control for these correlates may be biased.[16] In addition, they find the existence of pre-trends, even after considering the mechanical autocorrelation of the Bartik shocks over time, highlighting the importance of controlling for lagged growth.

Addressing identification concerns

In order address these identification concerns, I start by implementing two tests suggested by Goldsmith-Pinkham et al. (2017). First, I regress the gender-specific Bartik shocks with a number of start-year microregions' characteristics, and find similarly strong correlations. The results, shown in Appendix Table A.8, show that education levels (as measured by the shared of high-school educated in the adult population) is also a strong correlate of Bartik-style shocks in Brazil. They also reveal other correlates that may be specific to lower-income contexts, like urbanization rates and

[15] Preliminary work by Borusyak and Jaravel (2017) suggests that identification can in some cases also come from randomness in the national industry growth rates.

[16] Specifically, they find that IV estimates of the inverse elasticity of labor supply attenuate by over 25% after including base-year controls that are found to be correlated with the Bartik shock.

the demographic structure – the share of children and of prime-age adults in the population exhibit a strong connection with all the shocks.

Second, I assess the presence of pre-trends that could bias the estimates. In order to avoid capturing mechanical trends coming from the serial autocorrelation of the shocks,[17] the test first obtains the residuals of a regression of gender-specific employment growth on the corresponding shock. It then regresses the Bartik shocks from one decade in the future on these residuals. I repeat the exercise using growth in wages as an outcome. If future shocks are able to predict the fraction of the lagged outcomes that is not explained by contemporary shocks, it is taken as evidence of the existence of pre-trends. The results of these tests are shown in Table A.9. I find no statistically-significant evidence of pre-trends in the 1990s, but strong evidence in the 2000s.

In order to address the concerns raised by the correlation with start-year variables and the presence of pre-trends, I include in all my regressions a set of base-year and lagged controls. Part of these controls are directly informed by the tests described above. The base-year controls include population density, average log wages, average log housing rents, share of adults with high-school education or higher, shares of the population in six different age groups to account for demographic differences across localities, urbanization rate, formal and informal employment shares in the population, unemployment rate, and winter temperatures as a proxy of climate amenities.[18] The lagged-growth controls include the changes in the decade preceding the start year in population, wages, informal and formal employment, unemployment and urbanization rates. In my preferred specification I also use controls that seek to prevent comparing local economies that are structurally very dissimilar. These include employment shares of three broadly-defined industries: agriculture, manufacturing and government, and state fixed effects. My results reflect, therefore, comparisons of microregions within states, which have broadly similar industry structures.

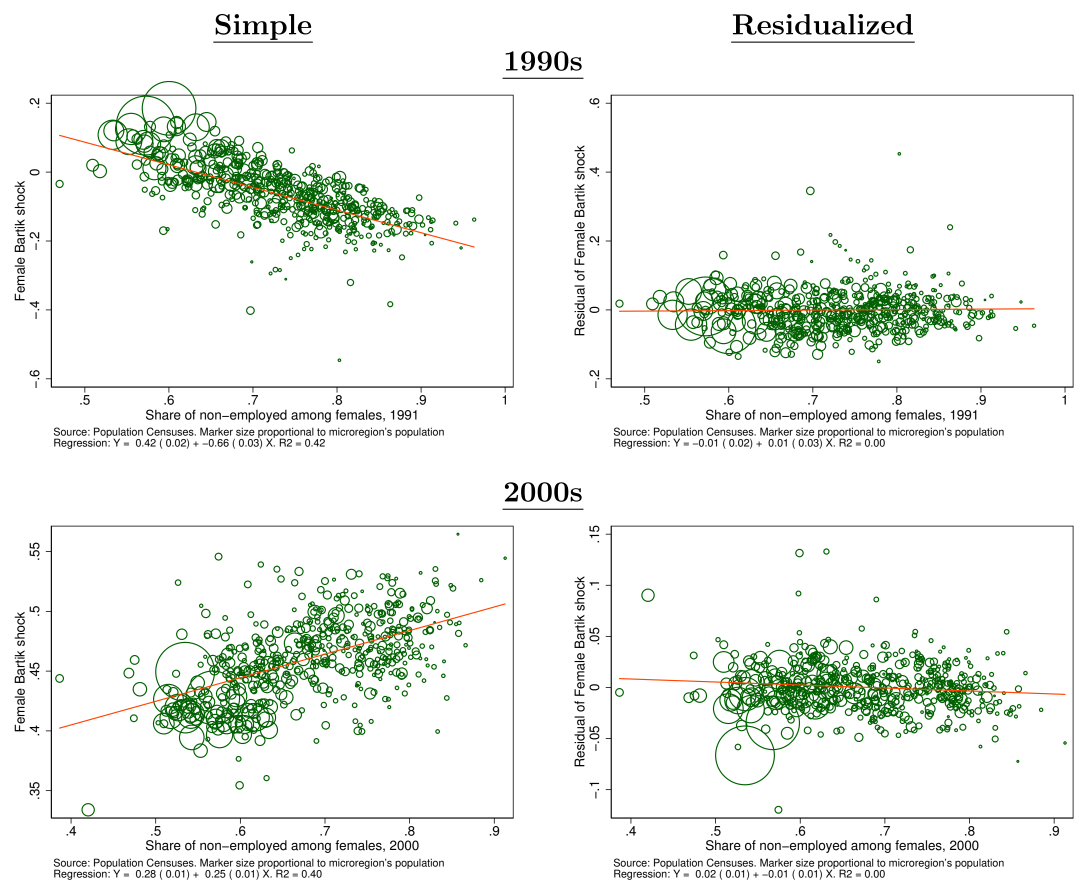
The coefficients on the gender-specific Bartik shocks can be given a causal interpretation under the selection-on-observables assumption. While by definition one can't rule-out the presence of potential unobservable confounders, looking at the correlation with other regional characteristics not included in the set of controls can be informative. If after controlling for the variables described above the shocks are still correlated with other start-year or lagged variables, identification would be put into question. I perform this exercise with a number of variables and find in all cases that the remaining variation of the shock is uncorrelated with characteristics not included as controls.

[17] Amior and Manning (2015) also highlight the role of serial correlation of demand shocks, showing that it can explain a large variation in local joblessness.

[18] Temperature appears to be a good proxy for time-invariant amenities that affect location decisions in Brazil. Oliveira and Pereda (2015) find that non-agricultural workers in Brazil have high willingness to pay for more temperate climate, and Chauvin et al. (2017) find that housing rents are larger in places with better climate amenities.

Figure 4 presents one example of these tests. Here I compare the Bartik shocks before and after controls with the share of non-employed individuals (i.e. non-participant or unemployed) in the adult female population for both decades. While the left column uses the Bartik shock measures without modifications, the right column uses the residuals of a regressions of the shocks on the controls. The evidence suggests that the included variables are effective at controlling for other potential confounders.[19]

Figure 4: Female Bartik shocks and base year female non-participation



Source: Own calculations using census data

4. Results

This section presents the empirical results of the paper. I estimate reduced-form regressions of the form described in equation 17, using decade-long changes for the 1990s and the 2000s. My units

[19] In this, as in most cases I tested, using only a small set of controls (population density, wages, education, informality and urbanization rates) already eliminates the correlation with the non-included control.

of observation are Brazilian microregions, and I use gender-specific Bartik shocks as measures of exogenous shifts in male and female labor demand.

I first look at the migration elasticity of households with respect to male and female labor demand shocks, and establish the existence of asymmetric responses. Second, I assess the effects of male and female shocks on housing rents, finding that male shocks lead to faster growth in local costs of living. Third, I evaluate the effects of male and female labor demand shocks on employment by gender, finding that male shocks tend to increase the employment gender gap and females shocks to decrease it. Fourth, I look at the net effect of gender-specific shocks on wages, finding that male shocks worsened the wage gap in both decades, and female shocks also worsened it during the 1990s. Finally, I look at the effects on the population of males and females that do not participate in the local labor force. I find that male shocks reduce non-participating male population, and increase non-participating female population. Conversely female shocks fail to reduce, or even have a positive effect the non-participant female population.

Both the shocks and the outcome variables are calculated for adults ages 15 through 64 who are not enrolled in an educational institution as students. In my preferred specification I exclude groups for whom wage determination is likely to follow a logic different from the standard market forces, including employers, career public servants, and member of security forces. In the robustness checks I relax these restrictions and all the key results are preserved. In all regressions I include the same set of controls described in Section 4 and cluster the standard errors at the mesoregion level (groupings of economically-related adjacent microregions) to address spatial autocorrelation concerns.

4.1. Gender-specific demand shocks and household migration

I begin by looking at the effects of gender-specific labor demand shocks on male and female migration. Table 1 shows the coefficients on gender-specific Bartik shocks in the regression model described in equation 17. The outcome variable is the log of the population of each subgroup that declared at the end of the decade (census year t) that they were living in a different microregion at the beginning of the decade (census year $t - 10$). Columns 1 and 2 present the effects of female and male shocks on own-gender migration. The next two columns report the effects of other-gender shocks. Column 3 presents the effect of male shocks on female migration, and column 4 the effects of female shocks on male migration. The last four columns present the test statistic and the p-value of Wald chi-square tests of the null hypothesis that the corresponding male and female coefficients are the same, based on seemingly unrelated regression models that include the correspondent female and male regressions. The difference that is being tested is indicated in the title of each column (for instance, the figures in the fifth column refer to tests of the difference of the coefficients in columns 1 and 2). For each outcome I also calculate the effect separately for two education subgroups: adult population with high-school degree or higher, and adult population without high-school degree. This serves as a reference to assess whether the aggregate gender effects could be affected by human capital heterogeneity within gender.[20] Unless otherwise specified, the tables of results for other outcomes follow the same layout.

Table 1: Effects of gender-specific demand shocks on migrant population

	Own-gender shocks		Other-gender shocks		Hypothesis tests (*χ^2 and p-val.*)			
	Females (1)	Males (2)	Females (3)	Males (4)	(1)-(2)	(3)-(4)	(1)-(4)	(2)-(3)
Panel A: 1991-2000								
All observations	3.90***	6.43***	6.61***	3.74***	8.17	10.83	2.25	1.11
	(0.70)	(1.30)	(1.31)	(0.69)	0.00	0.00	0.13	0.29
Less than high school	3.74***	6.51***	6.57***	3.63***	10.03	11.65	0.89	0.12
	(0.72)	(1.28)	(1.29)	(0.69)	0.00	0.00	0.35	0.73
High-school or higher	4.01***	7.69***	7.31***	3.95***	10.73	15.26	0.03	0.49
	(0.82)	(1.42)	(1.32)	(0.79)	0.00	0.00	0.87	0.48
Panel B: 2000-2010								
All observations	1.48	3.19**	2.82**	2.00	0.53	0.12	3.44	2.98
	(1.69)	(1.30)	(1.27)	(1.75)	0.47	0.73	0.06	0.08
Less than high school	1.90	3.09**	2.78**	2.31	0.22	0.03	1.10	1.00
	(1.78)	(1.38)	(1.31)	(1.86)	0.64	0.85	0.29	0.32
High-school or higher	0.82	3.91***	3.48***	1.01	1.76	1.02	0.07	0.83
	(1.72)	(1.30)	(1.33)	(1.80)	0.18	0.31	0.79	0.36

Note: Outcomes measured restricting the sample to individuals aged 15 through 64, excluding individuals in school, employers, civil servants, and public security. All regressions include a constant. Robust standard errors clustered at the mesoregion level in parentheses, except for the hypothesis tests. The hypothesis tests are Wald chi-square tests of the hypotheses of the type $H_0 : \beta_{males} - \beta_{females} = 0$ on SUR models including the respective female and male regressions. *** p<0.01, ** p<0.05, * p<0.1.

The results provide strong support for the assumption that couples tend to migrate together, and the prediction that they are more likely to migrate in response to changes in labor demand for males. First, the effect of male Bartik shocks on own-gender migration is significantly larger than the equivalent effect of female shocks. This is true in both decades, although the 2000s results are measured less precisely, consistent with the lower aggregate migration of that decade. Second, male shocks also have a larger effect on other-gender migration than female shocks do. And third, the

[20]Note that the population without high-school degree is still a significant majority of employees during this period, and variations in the Bartik shocks is disproportionally driven by variation in employment opportunity of this subpopulation.

size of the response of the migrant population of men and women to the same shock (e.g. male and female migration in response to male shocks) is very similar.

The difference in male-female migration elasticity were more pronounced at younger ages, strongest between ages 15 and 34 (see Appendix Figure A.3). Moreover, the disproportionally larger responses of females to male shocks were much smaller and statistically insignificant in the 2000s, the decade when migration dropped in the country as a whole. This suggests that the migration mechanisms highlighted in Section 2 were more prevalent in the 1990s, which should be kept in mind when iterpreting the rest of the results.

The composition of the migrant population is also consistent with the joint mobility assumption and the asymmetric response to male and female shocks. Table A.6 shows that while 57% of the adult population is married, 62% of the migrant adults are.[21] Among the population with less than high-school education, 69% is married in the aggregate, and 71% is married among the migrants. More importantly, if females staying behind was the norm in Brazilian internal economic migration, this would reflect on a disproportionally high share of males in the migrant population, particularly among the married migrants. But as shown in Table A.6, if anything, females are a larger share in the married migrant population. Males are a larger share in the migrant population only among singles. The fact that women migrated more than men over this period in spite relatively smaller own-gender migration elasticity suggests both that couples tend to move together, and that they tend to disproportionally follow males' work opportunities.

Moreover, it seems to be the case that females migrated more than males not because of, but in spite of their employment prospects. Appendix table A.7 reports aggregate economic outcomes separately for all individuals and for migrant individuals by gender and educational attainment category in 2000. While migrant women exhibit labor force participation rates and employment rates similar to the average, migrant males have lower non-participation and higher employment rates than the region as a whole. Migrant women without high-school education participate more in the labor force than the average, with a higher rate of failure at finding jobs as suggested by higher unemployment figures. Migrant women with high-school education tend to participate in the labor force less than the average, and still have higher unemployment rates. Migrant men participate more and have lower unemployment rates than the average in both educational attainment categories. In addition, migrant men tend to be disproportionally employed in the formal sector, and migrant

[21] An important caveat of looking at differences between married and single populations is that the census only provides contemporaneous information on marital status, that is, marital status at the beginning of the period is not observed. It is likely that marital status is endogenous to labor market shocks, since individuals' economic situation tend to affect their propensity to marry.

women disproportionally employed in the informal sector.

4.2. Effects on population and housing rents

The same gender asymmetries can be seen using log changes in population as the dependent variable (Table 2). A ten percent predicted increase in employment for men was associated with a 7.1 percent increase in male population in the 1990s and a 7.6 percent increase in the 2000s. Conversely, a ten percent predicted increase in employment for women corresponded to increases of 2.9 percent in 1990s and 0.9 percent in 2000s, both statistically insignificant. Migration responses appear to have been an important mechanism of adjustment to geographically heterogeneous changes in demand, particularly in the 1991-2000 period, a finding that is at odds with Dix-carneiro and Kovak (2016), who find little evidence of interregional migration in Brazil in response to a trade liberalization shock but consistent with Morten and Oliveira (2016), who find strong migration responses to changes in road infrastructure.

Table 2: Effects of gender-specific demand shocks on population

	Own-gender shocks		Other-gender shocks		Hypothesis tests *(χ^2 and p-val.)*			
	Females (1)	Males (2)	Females (3)	Males (4)	(1)-(2)	(3)-(4)	(1)-(4)	(2)-(3)
Panel A: 1991-2000								
All observations	0.29	0.71***	0.65**	0.33**	13.44	3.84	0.50	0.39
	(0.20)	(0.25)	(0.29)	(0.17)	0.00	0.05	0.48	0.53
Less than high school	0.16	0.97***	0.88***	0.20	21.38	13.57	0.29	0.63
	(0.24)	(0.24)	(0.30)	(0.19)	0.00	0.00	0.59	0.43
High-school or higher	0.56***	0.42	0.45	0.36	0.12	0.13	0.86	0.01
	(0.18)	(0.40)	(0.29)	(0.24)	0.73	0.72	0.35	0.92
Panel B: 2000-2010								
All observations	0.09	0.76***	0.75***	0.10	4.23	3.40	0.02	0.01
	(0.23)	(0.20)	(0.18)	(0.26)	0.04	0.07	0.90	0.92
Less than high school	-0.28	0.81***	0.75***	-0.56*	5.85	8.72	7.77	0.36
	(0.29)	(0.22)	(0.21)	(0.30)	0.02	0.00	0.01	0.55
High-school or higher	0.78**	1.24***	0.60	0.65	0.59	0.01	0.15	7.50
	(0.40)	(0.39)	(0.37)	(0.51)	0.44	0.93	0.70	0.01

Note: Outcomes measured restricting the sample to individuals aged 15 through 64, excluding individuals in school, employers, civil servants, and public security. All regressions include a constant. Robust standard errors clustered at the mesoregion level in parentheses, except for the hypothesis tests. The hypothesis tests are Wald chi-square tests of the hypotheses of the type $H_0 : \beta_{males} - \beta_{females} = 0$ on SUR models including the respective female and male regressions. *** p<0.01, ** p<0.05, * p<0.1.

The effects on population by schooling category also reveal the presence of potential composition effects. In spite of the lower migratory response of women, the population of females with high-school education or higher grew significantly in response to female labor demand shocks. Factors like increases in female education, reduction in family size, and faster urbanization rates contributed to significant growth in female labor force participation during this period (Scorzafave and Menezes-Filho 2005). A possible explanation for the coefficients by education group in column 1 of Table 2 is that females endogenously acquired more education in localities with better female labor prospects. Another is that, following negative shocks to local employment, the female population that left (following their husband's or looking for better opportunities for themselves) were disproportionally low-educated, so that the female employment left behind was positively selected. In my model workers are only heterogenous in gender but not in skills, so it is not informative of this margin of adjustment. How education and gender interact in the context of local labor markets and joint mobility frictions is a promising area for future research.

Table 3: Effects of gender-specific demand shocks on rents

Dependent Variable: Δ Avg. Log Rent Residuals			
Aggregate Shock	Female Shock	Male Shock	*Diff. Test* *(χ^2 and p-val.)*
(1)	(2)	(3)	(4)
0.41	0.01	0.63**	*4.25*
(0.31)	(0.27)	(0.31)	*0.04*

Note: Outcomes measured restricting the sample to households with rent data. All regressions include a constant. Robust standard errors clustered at the mesoregion level in parentheses, except for the hypothesis tests. Tests are Wald chi-square scores of the hypothesis $H_0 : \beta_{males} - \beta_{females} = 0$ on SUR models.
*** p<0.01, ** p<0.05, * p<0.1.

Given that male labor demand shocks have a larger effect on migration and population, the model predicts that it should also have a larger effect on housing demand and ultimately housing rents. The results for this outcomes are reported in Table 3. I only observe housing rents in the 1991 and 2010 census, so the coefficients on the table corresponds to regressions on differences over a 20-year period (in contrast with decade-long changes in all other tables). The dependent variable is the change in average log rent controlling for dwelling characteristics. Specifically, I run individual regressions of the log housing rent on a vector of characteristics of the property (see Appendix D), obtain the residuals, and average them at the microregion level to obtain the regional housing rents for each period.[22]

I find that, while male shocks had a significant, positive, and large effect on housing rents, the effects of female shocks was not distinguishable from zero. A ten percent expected increase in male employment was associated with a 6.3 percent increase in housing rents. Compared to female labor demand shocks, male shocks made Brazilian regions more expensive over this period.

4.3. Employment effects

I turn now to the effects on employment. Recall that, in the context of the model, the effect on own-employment is expected to be positive for both men and women but larger for men. This is true even in the absence of migration effects, because female employment is restricted by their larger labor force participation costs. The model also predicts the effects of other-gender shocks to be positive and larger for males.

The employment predictions of the model are generally supported by the data, as reported on Table 4. A 10 percent increase in predicted male employment leads to a 14.2 percent increase in actual employment in the 1990s, and 12.7 percent in the 2000s. The effects are driven by the low-education population. Meanwhile, a 10 percent increase in predicted female employment leads to a 6.9 percent increase in actual employment in the 1990s, and a 3.2, not statistically significant percent in the 2000s. Among women, the effects are driven by the population with high-school degree or higher.

A deviation from the the model's predictions is the observed negative effect of female shocks on male employment in the 2000s, which was concentrated in the low-education population. In the context of low migratory responses, this effect is ruled by input substitution in production in the theory. The negative coefficient suggest that low-education male labor may have been complementary to high-education female labor in this period. The labor force polarization literature in the U.S. has highlighted similar complementarities between high- and low-skilled workers (Autor and Dorn 2013; Autor et al. 2009). These potential interactions are not captured in a model that assumes away skills heterogeneity.

[22] All monetary variables in this paper are expressed in 2010 Reais, using INPC deflators published by the IBGE, and corrected using the method suggested in Corseuil and Foguel (2002).

Table 4: Effects of gender-specific demand shocks on employment

	Own-gender shocks		Other-gender shocks		Hypothesis tests (χ^2 *and p-val.)*			
	Females (1)	Males (2)	Females (3)	Males (4)	(1)-(2)	(3)-(4)	(1)-(4)	(2)-(3)
Panel A: 1991-2000								
All observations	0.69***	1.42***	0.85**	0.55***	12.84	0.87	0.97	4.43
	(0.20)	(0.27)	(0.39)	(0.20)	0.00	0.35	0.32	0.04
Less than high school	0.69***	1.66***	1.05**	0.44**	14.19	2.52	2.08	2.71
	(0.25)	(0.27)	(0.45)	(0.23)	0.00	0.11	0.15	0.10
High-school or higher	0.91***	0.80*	1.01***	0.43	0.04	1.60	1.55	0.19
	(0.24)	(0.48)	(0.38)	(0.32)	0.84	0.21	0.21	0.67
Panel B: 2000-2010								
All observations	0.32	1.27***	0.44	-0.72*	3.75	4.22	14.85	8.46
	(0.36)	(0.24)	(0.36)	(0.39)	0.05	0.04	0.00	0.00
Less than high school	0.09	1.27***	0.44	-1.23***	4.52	7.02	22.06	5.73
	(0.39)	(0.25)	(0.40)	(0.39)	0.03	0.01	0.00	0.02
High-school or higher	1.19**	1.20***	0.35	0.70	0.00	0.21	1.22	7.61
	(0.47)	(0.43)	(0.42)	(0.61)	0.99	0.65	0.27	0.01

Note: Outcomes measured restricting the sample to individuals aged 15 through 64, excluding individuals in school, employers, civil servants, and public security. All regressions include a constant. Robust standard errors clustered at the mesoregion level in parentheses, except for the hypothesis tests. The hypothesis tests are Wald chi-square tests of the hypotheses of the type $H_0 : \beta_{males} - \beta_{females} = 0$ on SUR models including the respective female and male regressions. *** p<0.01, ** p<0.05, * p<0.1.

In the aggregate, the gender employment gap was exacerbated by male-leaning local demand shocks and improved by female-leaning shocks during the period of analysis. This can be seen in Table 5, which directly measures the effects of the shocks on the log differences across decades in the gap, defined as the ratio of male to female employment rates. These effects are largely driven by the low-education population, with no statistically significant effects on the gap among individuals with high school education or higher.

Male and female Bartik shocks affect the gender employment gap at different margins. Appendix Figure A.4 depicts the predictive margins at different levels of the shocks, that is, the predicted effects on the gap if every microregion had had the same intensity of the shock holding all other actual characteristics as they were in practice. In both decades, male shock tend to reduce the employment gaps only at lower levels. Shocks above median intensity appear to have no effect on the gap. For females, the negative effects on the employment gap are concentrated on the higher levels. The gap appears to have little sensitivity to female shocks below median intensity.

Table 5: Effects on the employment gap

	1991-2000			2000-2010		
	Females	**Males**	*Diff. Test* *(χ^2 and p-val.)*	**Females**	**Males**	*Diff. Test* *(χ^2 and p-val.)*
	(1)	(2)	(3)	(4)	(5)	(6)
All observations	-2.37*	2.88*	*13.13*	-4.23***	3.45***	*26.05*
	(1.23)	(1.61)	*0.00*	(0.90)	(0.92)	*0.00*
Less than high school	-2.78**	3.35*	*12.58*	-4.46***	3.47***	*26.65*
	(1.27)	(2.00)	*0.00*	(0.90)	(1.02)	*0.00*
High-school or higher	-0.32	-0.08	*0.56*	-0.49	0.35	*3.42*
	(0.40)	(0.59)	*0.45*	(0.32)	(0.24)	*0.06*

Note: Outcomes measured restricting the sample to individuals aged 15 through 64, excluding individuals in school, employers, civil servants, and public security. All regressions include a constant. Robust standard errors clustered at the mesoregion level in parentheses, except for the hypothesis tests. The hypothesis tests are Wald chi-square tests of the hypotheses of the type $H_0 : \beta_{males} - \beta_{females} = 0$ on SUR models including the respective female and male regressions. *** p<0.01, ** p<0.05, * p<0.1.

4.4. Wages and participation effects

I turn now to the effects of gender-specific local demand shocks on wages and labor force participation. It is useful to look at both outcomes together in the context of the model, where wages are the key endogenous driver of labor force participation decisions. Decisions to sort into the workplace are also affected by the opportunity cost of participating, which is exogenously determined in the model.

My preferred wage measure controls for observable individual characteristics like education levels, age as a proxy of work experience, and race. Specifically, I calculate the residuals of individual-level Mincer-style regressions of log wages on individual characteristics (Mincer 1974). I then use the regional averages of these wage residuals for the sub-population of interest. The use of this formulation is fairly standard in the urban literature (e.g. Chauvin et al. 2017; Glaeser and Gottlieb 2009).

I find that, on average, local male wages increase more than local female wages in response to an equivalent shock in demand (Table 6). In the aggregate sample, which includes both education groups, the effect of own-gender shocks on female wages is not statistically different from zero, while the equivalent effect on male wages is. The difference across genders is only significant in the 1990s, when the migration effects are more likely to be present.

Table 6: Effects of gender-specific demand shocks on wages

	Own-gender shocks		Other-gender shocks		Hypothesis tests (χ^2 *and p-val.)*			
	Females (1)	Males (2)	Females (3)	Males (4)	(1)-(2)	(3)-(4)	(1)-(4)	(2)-(3)
Panel A: 1991-2000								
All observations	0.03	0.53***	0.35*	0.38***	8.35	0.04	5.54	1.33
	(0.14)	(0.18)	(0.20)	(0.09)	0.00	0.85	0.02	0.25
Less than high school	0.03	0.50***	0.35	0.37***	6.81	0.01	4.84	0.76
	(0.15)	(0.19)	(0.23)	(0.09)	0.01	0.93	0.03	0.38
High-school or higher	-0.25	0.07	-0.12	0.08	0.93	0.37	1.58	0.26
	(0.19)	(0.30)	(0.27)	(0.20)	0.34	0.54	0.21	0.61
Panel B: 2000-2010								
All observations	0.37	0.56***	0.26	0.33	0.27	0.04	0.04	2.15
	(0.26)	(0.21)	(0.20)	(0.27)	0.60	0.84	0.85	0.14
Less than high school	0.46	0.47**	0.17	0.27	0.00	0.05	0.38	1.71
	(0.35)	(0.22)	(0.25)	(0.27)	0.99	0.82	0.54	0.19
High-school or higher	0.18	0.59***	0.33	0.58*	1.20	0.39	2.02	1.07
	(0.29)	(0.22)	(0.23)	(0.30)	0.27	0.53	0.16	0.30

Note: Outcomes measured restricting the sample to individuals aged 15 through 64, excluding individuals in school, employers, civil servants, and public security. All regressions include a constant. Robust standard errors clustered at the mesoregion level in parentheses, except for the hypothesis tests. The hypothesis tests are Wald chi-square tests of the hypotheses of the type $H_0 : \beta_{males} - \beta_{females} = 0$ on SUR models including the respective female and male regressions. *** p<0.01, ** p<0.05, * p<0.1.

The fact that male shocks simultaneously lead to larger employment and wage effects than equivalent female shocks is hard to explain in an partial equilibrium setting. Larger employment effects suggest a more elastic labor supply curve, which in turn should imply relatively smaller wage effects. In general equilibrium, however, male shocks could have larger wage and employment effects than female shocks because of large compensating differentials for local costs of living. The fact that housing rents react to changes in male labor demand but not to changes in female demand supports this interpretation.

The combined wages and participation effects, however, cannot be fully accounted for by the assumptions of the model. Male shocks led to large immigration not only of males, but also of females, and this shift in supply should have generated a downwards pressure on the female wage. One explanation for why male shocks would not drive down female wages, still within the model, is again compensating differentials, since increases in male labor demand make the region more expensive for both members of the household. However, that explanation is at odds with the fact that the non-participant population of females increased in response to male shocks, particularly during the 1990s (Table 7). In the model, higher wages should have led to higher participation.

Table 7: Effects of gender-specific demand shocks on non-participant population

	Own-gender shocks		Other-gender shocks		Hypothesis tests *(χ^2 and p-val.)*			
	Females (1)	Males (2)	Females (3)	Males (4)	(1)-(2)	(3)-(4)	(1)-(4)	(2)-(3)
Panel A: 1991-2000								
All observations	0.26	-1.45***	0.58*	-0.43*	25.71	12.22	9.53	39.45
	(0.22)	(0.40)	(0.33)	(0.22)	0.00	0.00	0.00	0.00
Less than high school	0.06	-1.18***	0.80**	-0.64***	11.73	25.22	10.15	33.90
	(0.26)	(0.39)	(0.34)	(0.24)	0.00	0.00	0.00	0.00
High-school or higher	0.18	-1.48	0.01	-0.37	2.62	0.31	0.99	1.95
	(0.32)	(1.02)	(0.56)	(0.50)	0.11	0.58	0.32	0.16
Panel B: 2000-2010								
All observations	0.45**	-0.49	0.26	1.03***	4.65	2.95	2.85	5.42
	(0.20)	(0.37)	(0.19)	(0.39)	0.03	0.09	0.09	0.02
Less than high school	-0.03	-0.32	0.31	0.23	0.25	0.02	0.50	3.49
	(0.29)	(0.42)	(0.26)	(0.48)	0.62	0.88	0.48	0.06
High-school or higher	0.31	1.47*	0.56	0.31	1.28	0.05	0.00	2.36
	(0.59)	(0.76)	(0.47)	(0.93)	0.26	0.82	1.00	0.12

Note: Outcomes measured restricting the sample to individuals aged 15 through 64, excluding individuals in school, employers, civil servants, and public security. All regressions include a constant. Robust standard errors clustered at the mesoregion level in parentheses, except for the hypothesis tests. The hypothesis tests are Wald chi-square tests of the hypotheses of the type $H_0 : \beta_{males} - \beta_{females} = 0$ on SUR models including the respective female and male regressions. *** p<0.01, ** p<0.05, * p<0.1.

Other potential explanations requires me to step out the current assumptions of the model. One is the role of income effects. Indeed, an added worker effect, whereby married females reduce their labor force participation in response to increased wages or employment of married men, has been well-documented in the literature at the individual level (Fernandes and de Felicio 2005; Soares and Izaki 2002). This effect could potentially account for both the reduced participation rates and the increased female wages, as the female supply shifts backwards. A natural extension of the model is therefore to incorporate leisure or home production to the utility function to allow for income effects.

Other non-exclusive explanations for the observed results involve skill composition effects. As the population results in Table 2 suggest, women could have endogenously sorted into education in regions with higher female labor demand, pushing up female wages. If the added-worker effect was disproportionally prevalent among the low-education population, it could result in the females that remain in the labor force being positively selected (Olivetti and Petrongolo 2008). For example, Hunt (2002) showed that in East Germany following reunification the average wage gap fell significantly, but a large portion of this change was explained by involuntary exit from the labor force of low-skilled workers, who were disproportionally women.

Table 8: Effects on wage gaps

	1991-2000			2000-2010		
	Females	**Males**	*Diff. Test* (*χ^2 and p-val.*)	**Females**	**Males**	*Diff. Test* (*χ^2 and p-val.*)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 1991-2000						
All observations	0.34***	0.09	*2.22*	-0.22	0.48**	*3.16*
	(0.13)	(0.20)	*0.14*	(0.27)	(0.23)	*0.08*
Less than high school	0.33**	0.03	*3.15*	-0.10	0.39	*1.17*
	(0.15)	(0.19)	*0.08*	(0.34)	(0.24)	*0.28*
High-school or higher	0.35	0.10	*0.99*	0.34	0.21	*0.08*
	(0.27)	(0.42)	*0.32*	(0.36)	(0.29)	*0.78*

Note: Outcomes measured restricting the sample to individuals aged 15 through 64, excluding individuals in school, employers, civil servants, and public security. All regressions include a constant. Robust standard errors clustered at the mesoregion level in parentheses, except for the hypothesis tests. The hypothesis tests are Wald chi-square tests of the hypotheses of the type $H_0 : \beta_{males} - \beta_{females} = 0$ on SUR models including the respective female and male regressions. *** p<0.01, ** p<0.05, * p<0.1.

The introduction of an additional dimension of heterogeneity – education – makes the effects of the shocks on participation and wages potentially non-monotonic. For instance, while workers with the same education could be imperfect substitutes, high- and low-education workers could be complements (Moretti 2004). If skilled female workers and unskilled male workers complement each other in production, increases in demand for the former will result in higher wages and participation of low-skilled males, like those observed in the 1990s in Brazil. These effects could account for the fact that shocks to female labor demand affect the gender wage gap differently in different decades (Table 8), or that the predictive margins of these effects are non-linear and non-monotonic (as illustrated in Appendix Figure A.5). Further research is needed to better understand the way in which gender and education differences interact to shape outcomes in local labor markets.

4.5. Robustness

I perform multiple robustness checks of the results. First, I evaluate if the results vary without the exclusions from my main sample. Second, I test if the results are sensitive to the definitions of local labor markets and the definitions of industries. Third, I evaluate the sensitivity of the results to the inclusion of different sets of controls.

Results may be sensitive to the definition of labor markets, among other things due to spatial autocorrelation. Regions close to each other may have similar results, or outcomes may spillover to neighboring local markets. Concerns about potential geographic correlation of shocks is reduced by clustering all standard errors at the level of mesoregions, the next higher level of geography.

However, this does not solve the issue of neighbors' spillovers. I re-run the analysis using the definition of minimum comparable microregions from Dix-carneiro and Kovak (2016). This involves a coarser aggregation of municipalities as noted in Section 3.3, with the final sample including 411 microregions as opposed to 539 in my sample. The results are less precisely measured but still statistically significant in all the relevant cases, and all the findings discussed above hold.

My main specifications include all regions of Brazil in unweighted region-level regressions. Given the distribution of regional characteristics this implies that relatively small, frequently less urbanized regions, drive the results. To assess the extent to which the findings also hold in big urban centers I replicate the analysis restricting it to large urban conglomerates. Specifically, I use "Arranjos Populacionais" (IBGE 2016), which are groupings of core urban centers with municipalities closely integrated to them through work and education daily commuting. I consider both urban agglomerations and self-standing municipalities with large urban populations, and use the same correction described in Section 3.3 to account for changing administrative boundaries. Most of the key results of the analysis are also found in this urban centers sample. In this sample, non-employment for women also decreases in the 1990s following a male demand shock, although this reduction is still significantly smaller than the reduction in male non-employment. This is consistent with the view that local employment shocks in urban centers are less distortionary than shock in less urbanized regions, since tied-migrant females are more likely to find jobs in denser agglomerations.

I also verify that other smaller sources of that the industry definition used does not alter my results significantly. I take the industry definitions from Dix-carneiro and Kovak (2016) and replicate the analysis. The Bartik shocks calculated in with this industry definition are highly correlated with the ones calculated with the census definitions, and the regression results are unchanged in all the main specifications of interest.

The restrictions included in the sample do not seem to affect the results in any significant way either. The main conclusions are preserved if the sample includes only adult population aged 25 to 64 (that is, dropping the population aged 15 through 24 relative to my main sample), or include self-employed, government workers and domestic workers.

Adding and subtracting plausibly relevant controls – beyond the core baseline controls which include starting income levels, age structure, urbanization rate, and share of high-school educated population – also leave the results largely unchanged. An exception is the inclusion of base year share of non-employed men and women. After controlling for initial non-employment the discrepancy in the wage effects loses statistical significance. However, the differences in employment, population, and non-employment effects remain, and the non-employment effects among females are unambiguously positive and statistically significant. Consistent with the theory, low labor force participation among local residents does seem to be driving part of the wage effects. However, in the aggregate, I still find local labor supply of male labor to be more elastic than female labor due to larger male migration elasticity.

5. Welfare and policy implications

The results discussed above imply that male and female labor demand shocks can have very different welfare consequences. When local demand for female labor increases, firms on average are able to tap into a labor pool readily available in the region, which translates into higher employment for incumbent residents. In this context, local residents are able capture a larger share or the economic rents generated by the shock than workers living outside of the region and potential migrants. Because females have a more modest immigration effect than men, the pressure on housing prices, is not as high. As discussed by (Moretti 2011), in this kind of situation housing prices see limited increases and workers are likely to receive a larger fraction or the benefits than landlords.

The evidence presented in this paper also raises the possibility that female labor is less efficiently allocated across space than male labor. This implies that local labor demand shocks for women could potentially bring about aggregate efficiency gains to the national economy, reducing misallocation. This is a promising area for future research.

Welfare consequences of male labor demand shocks are very different. When local demand for male worker increases, there is a larger migratory response. The framework suggests that in this situation local workers are likely to share larger fractions of the economic rents with migrant workers and landlords. .

These patterns are important in many policy contexts, and in particular for regional development policies. These policies typically have as one of their main goals the generation of jobs for locals in underdeveloped regions. They are widespread throughout the globe (Kline and Moretti 2014b) and have been used in Brazil since at least the 1940s (Resende 2013; Cavalcanti Ferreira 2004). My findings suggest that the same policy can have very different effects depending on whether job growth favors male or female employment. If policies favor job creation for men over job creation for women, benefits to local residents are more likely to dissipate through migration and higher local costs of living. Moreover, the initial employment rates for men and women are likely to matter. “Place-making” policies may be more effective in improving the economic conditions of locals in places with lower levels of female employment.

6. Conclusion

This paper shows that the effects of local labor demand shocks can differ significantly by gender. I compare shifts in local labor demand for males and for females in the context of Brazil during the period 1991-2010. Male employment shocks, relative to equivalent female shocks, lead to larger increases in population, rents, and the gender economic gap.

I interpret these results in light of a spatial equilibrium model with gender-segmented labor markets. In this framework, the gender differences in population and employment effects are related to joint mobility constraints of married couples. Because men have in expectation lower opportunity costs of participating in the labor force than than women, male jobs prospects carry a larger weight in household location decisions than female job prospects. As a consequence, the migration elasticity of households is larger with respect to male than with respect to female demand shocks, and the former have larger effects on local population and prices than the latter. Because of tied migration, shocks in labor demand of one gender also affect the local labor supply of the other gender, with larger effects in male than in female shocks. The empirical results are largely consistent with the presence of this mechanism. Other non-exclusive margins of adjustments that appear to be at play are composition effects – related to females becoming more educated and supplying more labor over time – and income effects – which lead individuals to supply less labor if their partners' improve their work conditions. These are important areas for future research in local labor markets.

The presence of gender-differentiated migratory adjustments have important welfare implications. Because increases in local employment prospects for men place larger pressures on housing rents than equivalent shocks for women, part of the male wage effects captures compensating differentials for higher costs of living. It follows that while male shocks are more likely to benefit migrants and landlords and exacerbate the gender economic gap, female shocks are more likely to benefit local residents and reduce economic inequalities across genders. In addition, tied migration may lead to geographic misallocation of female labor, as tied-migrant women locate in regions that are not necessarily their individually optimal choice, and tied-stayer women take less advantage of jobs opportunities outside their place of residence than men do.

These findings have important policy consequences. Regional development and other "place-making" policies can lead to very different outcomes depending on how they affect labor demand for men and for women. In contexts with large gender and geographic disparities like Brazil during the period of study, this paper points towards significant advantages of expanding local female job opportunities.

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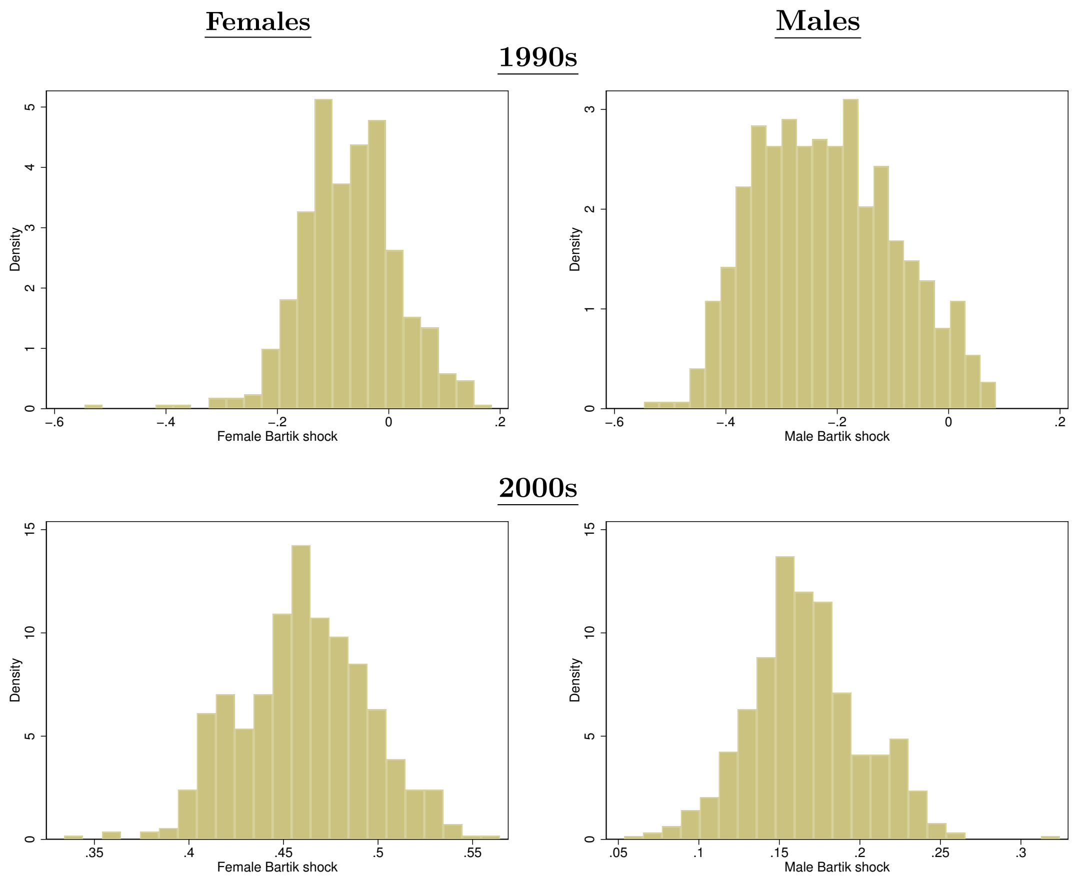
Appendix

A. Figures

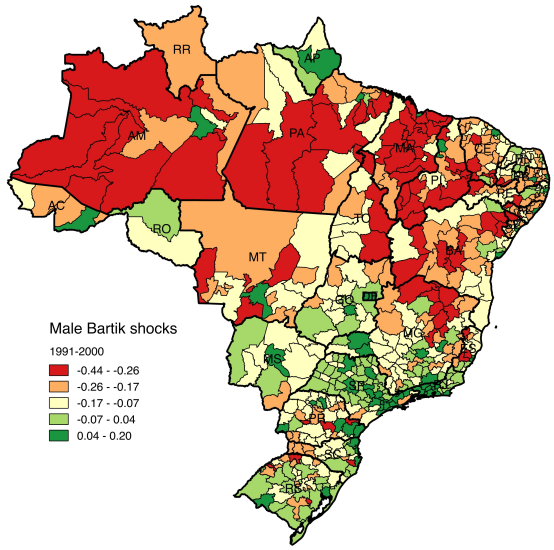
Figure A.1: Distributions of Gender-specific Bartik shocks



Source: Own calculations using census data

Figure A.2: Geographic distribution of gender-specific Bartik shocks, Brazil 1991-2000

Males



Females

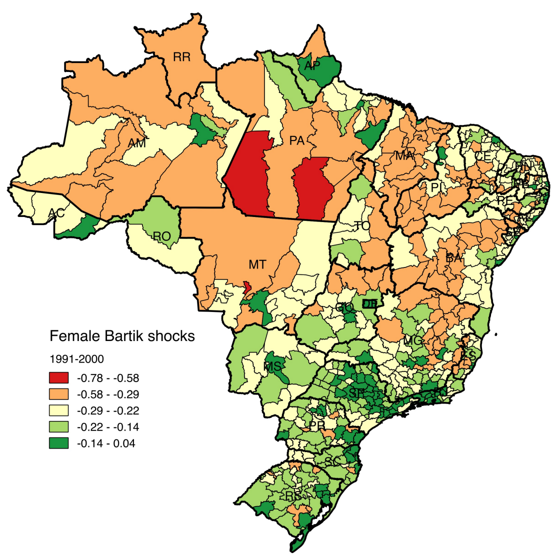
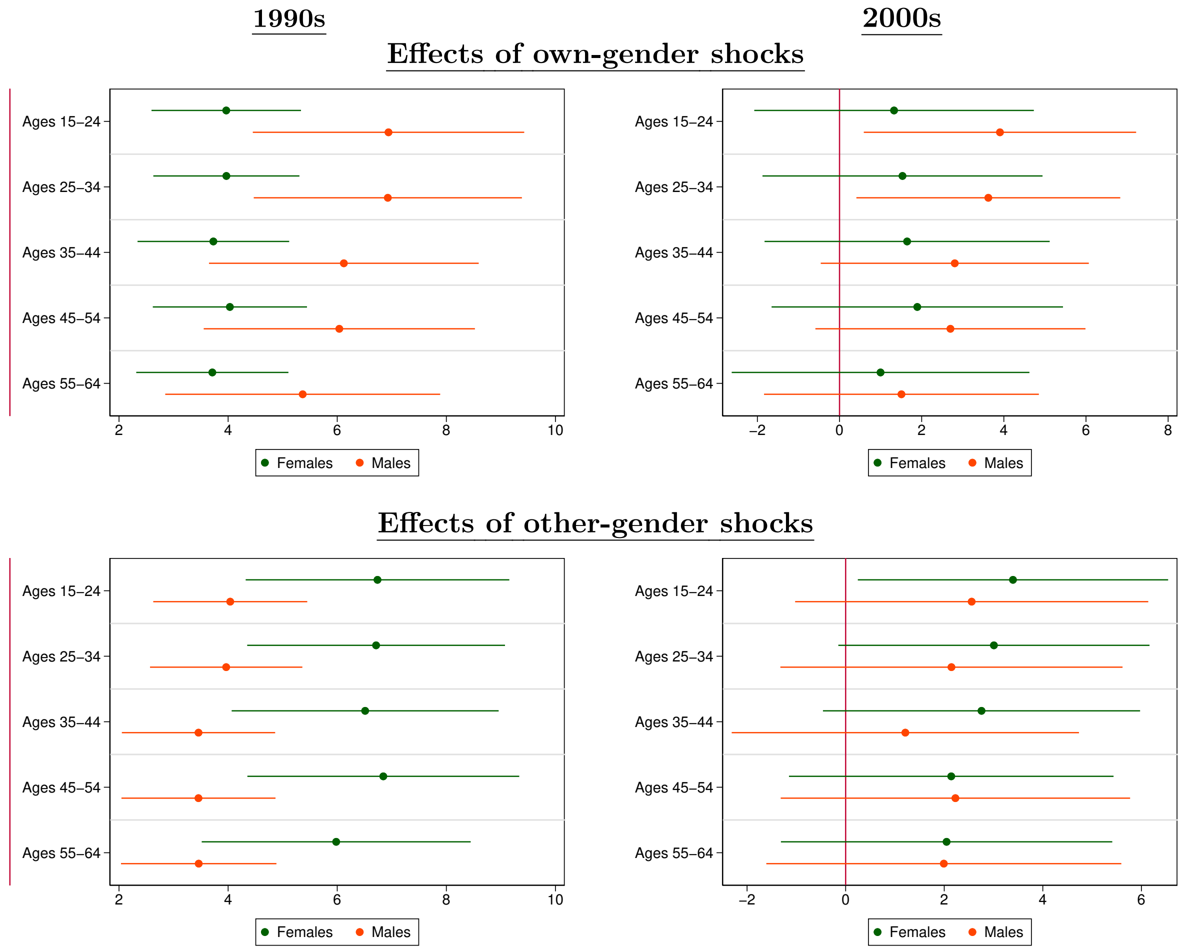


Figure A.3: Effects of gender-specific shocks on migrant population by age

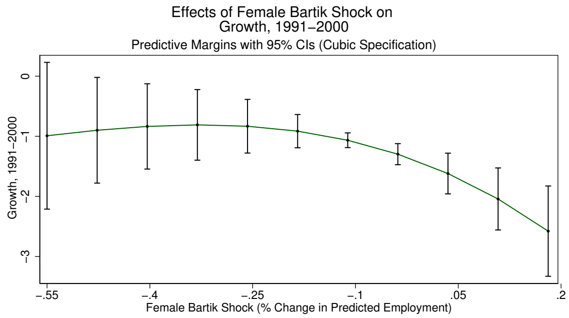


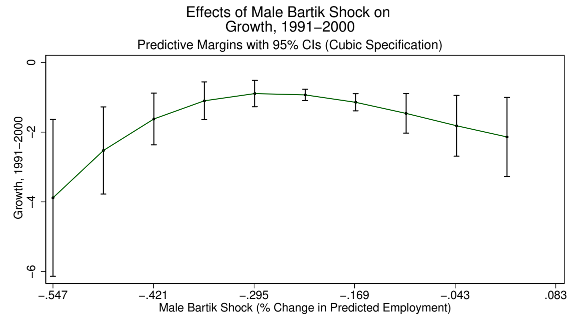
Source: Own calculations using census data

Figure A.4: Effects of gender-specific shocks on the employment gap, predictive margins

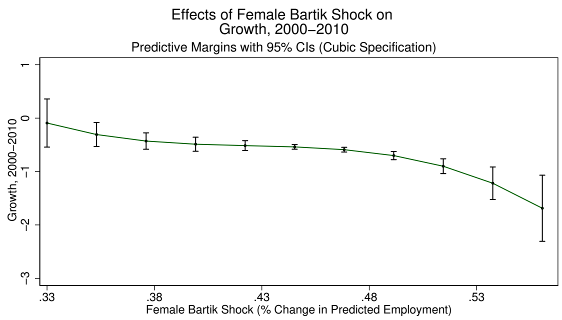
Female shocks **Male shocks**

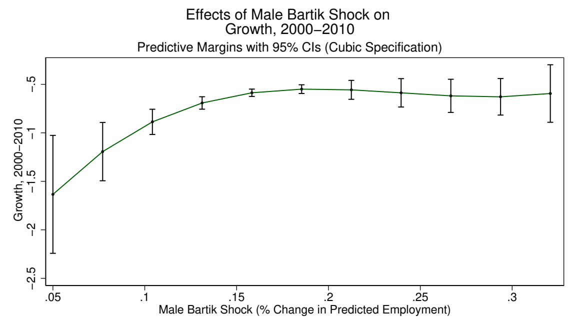
1990s





2000s



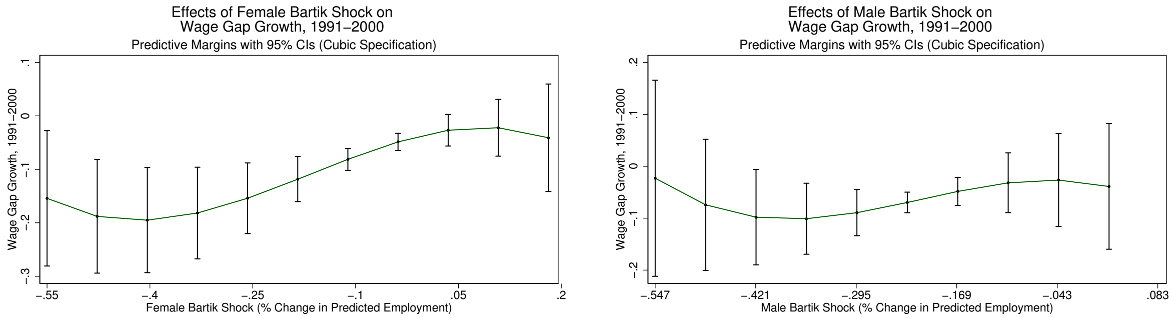


Source: Own calculations using census data

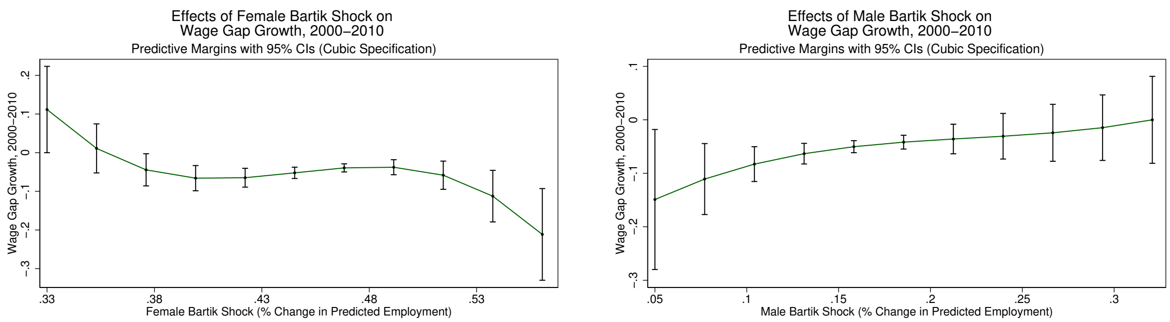
Figure A.5: Effects of gender-specific shocks on the wage gap, predictive margins

Female shocks | **Male shocks**

1990s

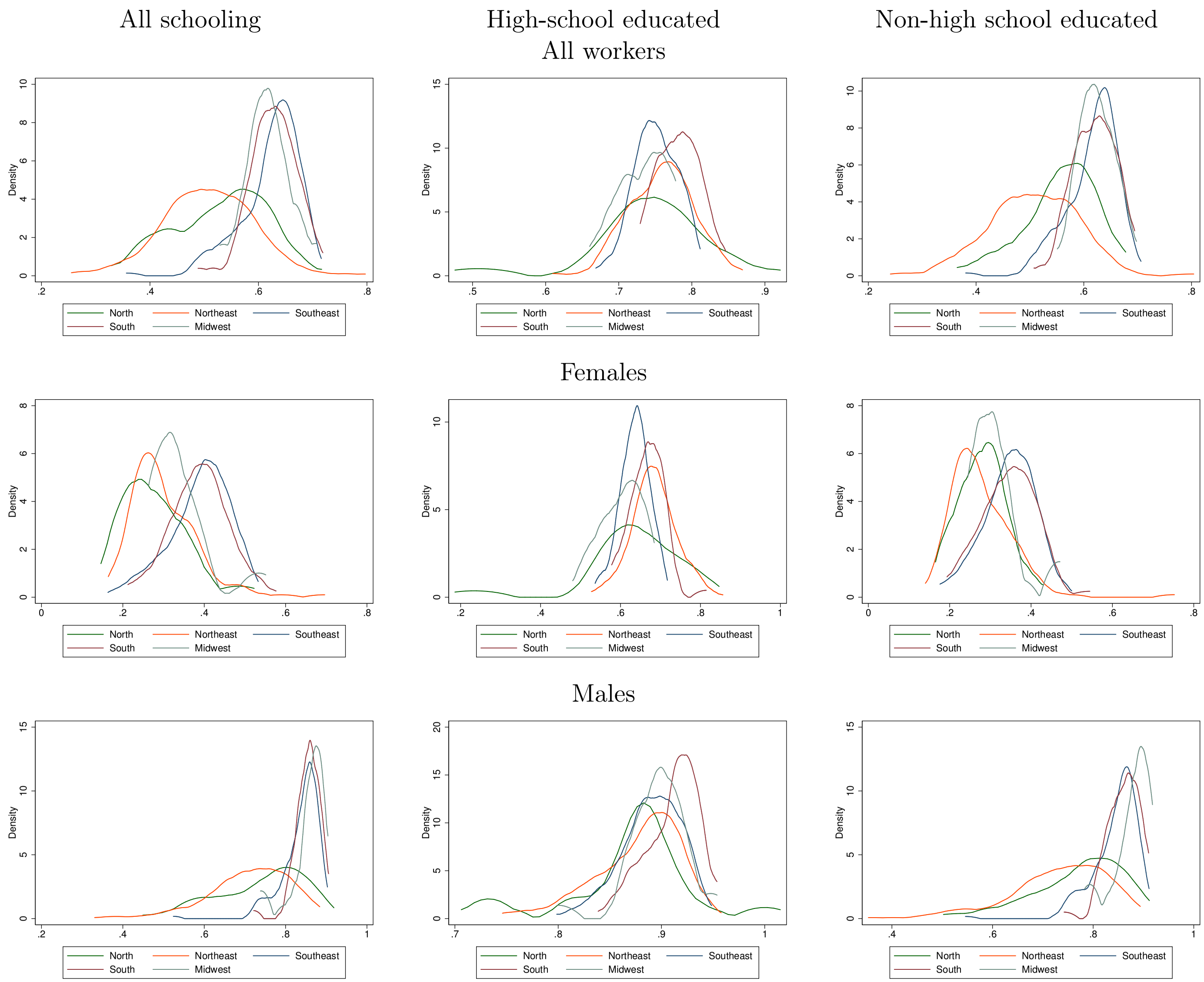


2000s



Source: Own calculations using census data

Figure A.6: Labor force participation across microregions in Brazilian macro-regions, 2000



Source: Own calculations using data from the 2000 demographic census.

B. Tables

Table A.1: Summary statistics, 1990s

	Mean	Std. Dev.	Min	Max
Shocks				
Bartik shocks, males	-0.07	0.09	-0.55	0.19
Bartik shocks, females	-0.22	0.12	-0.55	0.08
Main outcomes				
Δ_{91-00} Population	0.11	0.13	-0.46	0.93
Δ_{91-00} Female employment	0.31	0.21	-0.49	1.28
Δ_{91-00} Male employment	-0.06	0.2	-1.01	0.82
Δ_{91-00} Female average wage residual	0.01	0.17	-0.65	0.74
Δ_{91-00} Male average wage residual	-0.03	0.15	-0.66	0.37
Base year (1991) controls				
Log of population density	3.17	1.46	-1.65	8.51
Average log wage residual	-0.23	0.31	-1.1	0.74
Average temperature in the winter (C°)	20.86	4.16	11.83	27.25
Share of High-school educated	0.09	0.05	0	0.3
Formally-employed share in adult population	0.19	0.12	0.01	0.5
Informally-employed share in adult population	0.36	0.08	0.16	0.58
Unemployment rate	0.04	0.02	0	0.16
Share of population aged 0-14	0.37	0.06	0.27	0.53
Share of population aged 15-24	0.19	0.01	0.16	0.23
Share of population aged 25-34	0.15	0.02	0.1	0.2
Share of population aged 35-44	0.11	0.02	0.07	0.14
Share of population aged 45-44	0.07	0.01	0.05	0.11
Share of population aged 55-64	0.05	0.01	0.01	0.08
Urbanization rate	0.6	0.2	0.14	1
Share of employment in agriculture	0.45	0.21	0.01	0.92
Share of employment in manufacturing	0.1	0.08	0.01	0.52
Share of employment in government	0.03	0.01	0	0.15
Lagged changes controls				
Δ_{80-91} Population	0.23	0.22	-0.17	2.99
Δ_{80-91} Wage residual	-0.03	0.14	-0.56	0.46
Δ_{80-91} Formal employment	0.03	0.04	-0.1	0.21
Δ_{80-91} Informal employment	0	0.05	-0.21	0.17
Δ_{80-91} Unemployment rate	0.02	0.02	-0.19	0.14
Δ_{80-91} Urbanization rate	0.11	0.06	-0.2	0.48

Source: Own calculations with population censuses of 1980, 1991 and 2000. Outcomes calculated for individuals aged 15-64. N=539.

Table A.2: Summary statistics, 2000s

	Mean	Std. Dev.	Min	Max
Shocks				
Bartik shocks, males	0.46	0.03	0.33	0.56
Bartik shocks, females	0.17	0.04	0.05	0.32
Main outcomes				
Δ_{00-10} Population	0.18	0.11	-0.18	0.77
Δ_{00-10} Female employment	0.48	0.17	-0.07	1.35
Δ_{00-10} Male employment	0.2	0.13	-0.33	0.82
Δ_{00-10} Female average wage residual	0.03	0.11	-0.36	0.3
Δ_{00-10} Male average wage residual	0.03	0.12	-0.46	0.31
Base year (2000) controls				
Log of population density	3.29	1.46	-1.5	8.6
Average log wage residual	-0.26	0.26	-1.05	0.38
Average temperature in the winter (C°)	20.86	4.16	11.83	27.25
Share of High-school educated	0.15	0.07	0.02	0.38
Formally-employed share in adult population	0.17	0.1	0.01	0.48
Informally-employed share in adult population	0.34	0.06	0.15	0.51
Unemployment rate	0.13	0.04	0.03	0.26
Share of population aged 0-14	0.32	0.05	0.21	0.49
Share of population aged 15-24	0.2	0.02	0.16	0.24
Share of population aged 25-34	0.15	0.02	0.11	0.19
Share of population aged 35-44	0.12	0.02	0.08	0.17
Share of population aged 45-44	0.09	0.02	0.04	0.13
Share of population aged 55-64	0.06	0.01	0.03	0.1
Urbanization rate	0.67	0.18	0.19	1
Share of employment in agriculture	0.37	0.19	0	0.84
Share of employment in manufacturing	0.11	0.07	0.01	0.49
Share of employment in government	0.03	0.02	0.01	0.12
Lagged changes controls				
Δ_{91-00}Population	0.11	0.13	-0.46	0.93
Δ_{91-00}Wage residual	-0.03	0.14	-0.61	0.34
Δ_{91-00} Formal employment	-0.01	0.04	-0.13	0.1
Δ_{91-00} Informal employment	-0.02	0.06	-0.24	0.1
Δ_{91-00} Unemployment rate	0.08	0.03	-0.02	0.21
Δ_{91-00} Urbanization rate	0.07	0.05	-0.05	0.49

Source: Own calculations with population censuses of 1991, 2000 and 2010. Outcomes calculated for individuals aged 15-64. N=539.

Table A.3: Correlations, 1990s

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	Bartik shocks, males	1.00																							
2	Bartik shocks, females	0.87	1.00																						
3	Δ_{91-00} Population	0.26	0.38	1.00																					
4	Δ_{91-00} Female employment	0.07	0.03	0.56	1.00																				
5	Δ_{91-00} Male employment	0.49	0.59	0.73	0.55	1.00																			
6	Δ_{91-00} Female average wage residual	-0.11	-0.13	-0.25	-0.33	-0.35	1.00																		
7	Δ_{91-00} Male average wage residual	0.20	0.16	-0.16	-0.05	0.01	0.52	1.00																	
8	Log of population density	0.50	0.58	0.04	-0.28	0.15	0.23	0.15	1.00																
9	Average log wage residual	0.33	0.47	0.48	0.36	0.57	-0.74	-0.40	-0.02	1.00															
10	Average temperature in the winter ($C°$)	-0.42	-0.45	0.16	0.07	-0.25	0.02	-0.42	-0.34	-0.18	1.00														
11	Share of High-school educated	0.70	0.86	0.28	-0.02	0.49	-0.18	0.14	0.56	0.45	-0.39	1.00													
12	Formally-employed share in adult population	0.64	0.84	0.27	-0.05	0.50	-0.20	0.11	0.54	0.55	-0.58	0.83	1.00												
13	Informally-employed share in adult population	-0.55	-0.75	-0.21	0.01	-0.38	0.16	-0.10	-0.53	-0.46	0.53	-0.74	-0.91	1.00											
14	Unemployment rate	0.02	0.16	0.23	0.03	0.02	-0.14	-0.28	0.08	0.14	0.28	0.14	0.04	-0.25	1.00										
15	Share of population aged 0-14	-0.59	-0.67	0.06	0.11	-0.34	-0.05	-0.48	-0.49	-0.18	0.73	-0.68	-0.72	0.59	0.31	1.00									
16	Share of population aged 15-24	-0.05	0.03	0.12	0.11	0.13	-0.17	-0.09	-0.01	0.15	0.24	0.03	-0.10	0.11	0.18	0.16	1.00								
17	Share of population aged 25-34	0.59	0.74	0.20	0.13	0.56	-0.28	0.29	0.31	0.56	-0.63	0.75	0.80	-0.66	-0.15	-0.82	0.02	1.00							
18	Share of population aged 35-44	0.65	0.72	0.06	0.01	0.45	-0.13	0.38	0.40	0.39	-0.73	0.72	0.78	-0.64	-0.28	-0.92	-0.25	0.90	1.00						
19	Share of population aged 45-44	0.46	0.44	-0.23	-0.19	0.11	0.16	0.47	0.37	-0.03	-0.66	0.44	0.50	-0.41	-0.41	-0.89	-0.41	0.55	0.78	1.00					
20	Share of population aged 55-64	0.36	0.33	-0.27	-0.25	0.04	0.32	0.47	0.41	-0.21	-0.61	0.32	0.40	-0.32	-0.40	-0.80	-0.49	0.37	0.62	0.89	1.00				
21	Urbanization rate	0.69	0.88	0.34	-0.01	0.52	-0.21	0.10	0.45	0.53	-0.35	0.82	0.84	-0.70	0.14	-0.65	0.02	0.75	0.71	0.43	0.31	1.00			
22	Share of employment in agriculture	-0.75	-0.96	-0.40	0.00	-0.56	0.13	-0.10	-0.58	-0.50	0.39	-0.87	-0.88	0.78	-0.21	0.66	-0.05	-0.74	-0.69	-0.40	-0.31	-0.92	1.00		
23	Share of employment in manufacturing	0.45	0.64	0.26	-0.01	0.41	-0.16	-0.01	0.47	0.47	-0.42	0.52	0.78	-0.71	0.03	-0.49	-0.11	0.59	0.56	0.30	0.24	0.59	-0.70	1.00	
24	Share of employment in government	0.06	0.35	0.25	-0.03	0.29	-0.04	0.05	0.12	0.19	-0.07	0.47	0.39	-0.40	0.27	-0.24	0.15	0.29	0.19	0.10	0.07	0.42	-0.45	0.08	1.00

Note: Own-calculations based on population censuses of 1991 and 2000

Table A.4: Correlations, 2000s

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	Bartik shocks, males	1.00																							
2	Bartik shocks, females	-0.74	1.00																						
3	Δ_{00-10} Population	-0.17	0.18	1.00																					
4	Δ_{00-10} Female employment	0.20	-0.22	0.56	1.00																				
5	Δ_{00-10} Male employment	-0.39	0.38	0.76	0.53	1.00																			
6	Δ_{00-10} Female average wage residual	-0.06	0.08	-0.08	-0.14	-0.03	1.00																		
7	Δ_{00-10} Male average wage residual	-0.07	0.13	-0.18	-0.22	-0.09	0.79	1.00																	
8	Log of population density	-0.52	0.56	-0.04	-0.36	0.14	0.10	0.05	1.00																
9	Average log wage residual	-0.33	0.37	0.14	0.24	0.27	-0.07	0.02	0.11	1.00															
10	Average temperature in the winter ($C°$)	0.14	-0.15	0.46	0.17	0.18	-0.26	-0.36	-0.33	-0.40	1.00														
11	Share of High-school educated	-0.61	0.71	-0.02	-0.21	0.20	0.23	0.32	0.54	0.62	-0.45	1.00													
12	Formally-employed share in adult population	-0.57	0.56	-0.08	-0.21	0.14	0.26	0.37	0.50	0.70	-0.65	0.86	1.00												
13	Informally-employed share in adult population	0.54	-0.44	0.01	0.07	-0.33	0.14	0.04	-0.37	-0.23	0.21	-0.40	-0.46	1.00											
14	Unemployment rate	-0.38	0.43	0.16	-0.01	0.36	-0.29	-0.20	0.17	0.09	0.21	0.19	0.02	-0.57	1.00										
15	Share of population aged 0-14	0.41	-0.48	0.37	0.38	0.07	-0.44	-0.50	-0.49	-0.37	0.67	-0.71	-0.75	0.18	0.17	1.00									
16	Share of population aged 15-24	0.09	-0.08	0.43	0.18	0.20	-0.39	-0.39	-0.14	-0.17	0.69	-0.32	-0.46	0.06	0.39	0.67	1.00								
17	Share of population aged 25-34	-0.47	0.48	0.05	-0.01	0.25	0.26	0.30	0.35	0.74	-0.43	0.73	0.77	-0.17	0.02	-0.66	-0.27	1.00							
18	Share of population aged 35-44	-0.38	0.46	-0.27	-0.20	0.00	0.44	0.51	0.39	0.59	-0.73	0.76	0.84	-0.19	-0.18	-0.92	-0.70	0.77	1.00						
19	Share of population aged 45-44	-0.29	0.37	-0.44	-0.35	-0.15	0.46	0.51	0.42	0.33	-0.75	0.63	0.70	-0.15	-0.26	-0.94	-0.81	0.51	0.90	1.00					
20	Share of population aged 55-64	-0.08	0.13	-0.58	-0.44	-0.32	0.39	0.42	0.26	-0.15	-0.52	0.24	0.28	-0.03	-0.31	-0.75	-0.76	0.08	0.55	0.80	1.00				
21	Urbanization rate	-0.66	0.73	0.07	-0.23	0.26	0.26	0.36	0.44	0.63	-0.33	0.86	0.82	-0.36	0.25	-0.64	-0.25	0.73	0.70	0.54	0.17	1.00			
22	Share of employment in agriculture	0.79	-0.80	-0.15	0.19	-0.32	-0.18	-0.23	-0.56	-0.63	0.36	-0.86	-0.83	0.41	-0.30	0.61	0.20	-0.75	-0.67	-0.50	-0.10	-0.90	1.00		
23	Share of employment in manufacturing	-0.53	0.29	0.09	-0.01	0.17	0.14	0.12	0.38	0.52	-0.40	0.50	0.70	-0.31	-0.09	-0.42	-0.28	0.53	0.52	0.40	0.08	0.52	-0.62	1.00	
24	Share of employment in government	-0.35	0.22	0.11	-0.13	0.15	-0.11	-0.05	0.02	-0.08	0.21	0.08	-0.01	-0.27	0.37	0.07	0.14	-0.02	-0.14	-0.16	-0.07	0.08	-0.14	-0.18	1.00

Note: Own-calculations based on population censuses of 2000 and 2010

Table A.5: Population and work in Brazil between 1991 and 2000

	All education levels			Less than high-school			High-school or higher		
	All	**Male**	**Female**	**All**	**Male**	**Female**	**All**	**Male**	**Female**
Panel A: Levels in 1991									
Wages (in 2010 Reais)									
Working-age population	88,770,975	43,466,944	45,304,030	64,779,259	32,309,153	32,470,104	13,433,827	6,234,115	7,199,712
Non-participation rate	39.40%	16.39%	61.48%	40.11%	12.73%	67.36%	19.89%	6.64%	31.37%
Employment rate	57.54%	80.08%	35.92%	56.81%	83.51%	30.24%	76.83%	90.29%	65.17%
Labor force	53,794,919	36,341,883	17,453,036	38,793,230	28,196,008	10,597,221	10,761,475	5,820,313	4,941,162
Formality rate	51.60%	49.67%	55.62%	43.91%	43.73%	44.37%	76.76%	74.64%	79.25%
Informality rate	43.36%	46.11%	37.63%	50.95%	51.96%	48.27%	19.15%	22.08%	15.71%
Unemployment rate	5.04%	4.22%	6.75%	5.14%	4.31%	7.36%	4.09%	3.29%	5.04%
Panel B: Changes 1991-2000									
Working-age population	21.04%	21.07%	21.01%	-10.56%	-9.21%	-11.92%	51.56%	48.69%	53.98%
Non-participation rate	-3.41%	5.21%	-11.67%	-4.24%	4.20%	-12.13%	-1.53%	2.14%	-5.14%
Employment rate	-3.80%	-11.62%	3.70%	-2.19%	-9.85%	4.91%	-4.38%	-6.37%	-2.15%
Labor force	26.52%	14.64%	47.48%	-3.71%	-14.15%	19.69%	53.46%	46.38%	61.20%
Formality rate	-10.01%	-7.92%	-14.26%	-7.85%	-5.87%	-11.76%	-16.30%	-13.58%	-19.41%
Informality rate	-0.98%	-0.54%	-0.05%	-1.83%	-1.14%	-2.37%	9.13%	8.86%	9.87%
Unemployment rate	10.99%	8.46%	14.31%	9.69%	7.01%	14.13%	7.17%	4.71%	9.53%

Note: Own calculations from data of the 1991 and 2000 population censuses. For working age population and labor force the changes are measures as log-differences. For all other variables the changes are simple differences of the rates across census years.

Table A.6: Geographic Mobility working-age population in Brazil 1991-2000

	All education levels			Less than high-school			High-school or higher		
	All	**Male**	**Female**	**All**	**Male**	**Female**	**All**	**Male**	**Female**
Panel A: Totals									
Population aged 15-65	109,561,279	53,664,398	55,896,881	58,288,370	29,467,303	28,821,067	22,497,118	10,144,649	12,352,469
Married share	56.96%	56.93%	56.99%	68.56%	67.49%	69.65%	59.11%	63.27%	55.69%
Singles share	43.04%	43.07%	43.01%	31.44%	32.51%	30.35%	40.89%	36.73%	44.31%
Migrant population aged 15-65	24,501,659	11,970,129	12,531,530	13,739,906	6,887,839	6,852,067	4,901,727	2,265,163	2,636,564
Share of migrants in total population	22.36%	22.31%	22.42%	23.57%	23.37%	23.77%	21.79%	22.33%	21.34%
Married share in migrant population	61.64%	61.32%	61.96%	71.22%	69.52%	72.92%	65.26%	68.56%	62.43%
Singles share in migrant population	38.36%	38.68%	38.04%	28.78%	30.48%	27.08%	34.74%	31.44%	37.57%
Panel B: By age groups									
Population aged 15-24	34,089,000	17,075,229	17,013,771	12,437,473	6,527,441	5,910,032	4,718,610	1,989,689	2,728,921
Migrant share	23.43%	21.57%	25.31%	29.06%	25.74%	32.73%	21.37%	20.05%	22.33%
Population aged 25-34	26,857,658	13,171,168	13,686,490	15,719,162	8,102,705	7,616,458	7,108,166	3,103,490	4,004,675
Migrant share	28.20%	27.88%	28.50%	29.62%	28.99%	30.29%	26.11%	25.98%	26.20%
Population aged 35-49	31,501,553	15,269,366	16,232,187	19,407,577	9,648,094	9,759,483	7,971,970	3,701,254	4,270,716
Migrant share	20.60%	21.84%	19.44%	20.59%	21.54%	19.66%	20.45%	22.36%	18.80%
Population aged 50-64	17,113,068	8,148,636	8,964,433	10,724,157	5,189,064	5,535,094	2,698,372	1,350,215	1,348,157
Migrant share	14.32%	15.71%	13.04%	13.74%	15.04%	12.51%	15.08%	17.20%	12.97%
Panel B: By Marital status									
Married population	62,405,772	30,552,713	31,853,059	39,960,041	19,887,395	20,072,647	13,297,914	6,418,211	6,879,704
Migrant share	24.20%	24.02%	24.37%	24.49%	24.08%	24.89%	24.06%	24.20%	23.92%
Single population	47,155,507	23,111,685	24,043,822	18,328,329	9,579,908	8,748,420	9,199,203	3,726,438	5,472,765
Migrant share	19.93%	20.03%	19.83%	21.58%	21.92%	21.21%	18.51%	19.11%	18.10%

Note: Own calculations from data of the 2000 population census. A person is considered a migrant if it they moved to their current municipality of residence over the previous 10 years. Age groups, marital status and schooling attainment correspond to the year 2000 (this information is not available for the pre-migration period).

Table A.7: Migrant population and work in Brazil, 2000

	All education levels			Less than high-school			High-school or higher		
	All	**Male**	**Female**	**All**	**Male**	**Female**	**All**	**Male**	**Female**
Panel A: All individuals									
Working-age population	109,561,280	53,664,399	55,896,880	58,288,370	29,467,304	28,821,068	22,497,118	10,144,648	12,352,469
Non-participation rate	35.99%	21.60%	49.80%	35.87%	16.94%	55.23%	18.36%	8.77%	26.23%
Employment rate	53.75%	68.45%	39.63%	54.62%	73.66%	35.15%	72.45%	83.93%	63.02%
Labor force	70,128,808	42,071,072	28,057,735	37,379,901	24,476,897	12,903,005	18,366,590	9,254,582	9,112,007
Formality rate	41.59%	41.74%	41.36%	36.05%	37.86%	32.61%	60.46%	61.06%	59.84%
Informality rate	42.38%	45.57%	37.58%	49.12%	50.82%	45.90%	28.28%	30.94%	25.59%
Unemployment rate	16.03%	12.68%	21.06%	14.83%	11.32%	21.49%	11.26%	8.00%	14.57%
Panel B: Migrants									
Working-age population	24,501,659	11,970,129	12,531,531	13,739,907	6,887,839	6,852,067	4,901,727	2,265,162	2,636,564
Non-participation rate	32.75%	16.68%	48.10%	32.63%	12.75%	52.61%	19.28%	7.85%	29.11%
Employment rate	56.46%	73.61%	40.09%	56.90%	77.68%	36.00%	71.62%	85.89%	59.35%
Labor force	16,477,140	9,973,510	6,503,631	9,256,945	6,009,896	3,247,048	3,956,450	2,087,323	1,869,126
Formality rate	41.87%	44.57%	37.73%	37.41%	41.13%	30.51%	58.86%	62.00%	55.36%
Informality rate	42.09%	43.78%	39.51%	47.05%	47.90%	45.46%	29.87%	31.21%	28.37%
Unemployment rate	16.04%	11.66%	22.76%	15.55%	10.97%	24.03%	11.27%	6.79%	16.28%

Note: Own calculations from data of the 2000 population census. A person is considered a migrant if it they moved to their current municipality of residence over the previous 10 years.

Table A.8: Gender-specific Bartik shocks and start-year characteristics

	1991-2000 shocks		2000-2010 shocks	
	Females	Males	Females	Males
	(1)	(2)	(3)	(4)
Log population density	0.01***	0.01***	-0.00***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Log wage residuals	0.01	0.00	0.01	0.02*
	(0.02)	(0.02)	(0.01)	(0.01)
Average winter temperature	-0.00*	-0.00**	-0.00**	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
Share of high-school educated	0.59***	0.60***	-0.01	0.14***
	(0.12)	(0.11)	(0.04)	(0.04)
Formality rate	-0.18	0.08	0.00	-0.16***
	(0.13)	(0.12)	(0.04)	(0.04)
Informality rate	0.00	0.01	0.18***	-0.07*
	(0.13)	(0.11)	(0.03)	(0.03)
Unemployment rate	0.01	0.43**	-0.00	0.12**
	(0.23)	(0.19)	(0.05)	(0.05)
Population share aged 0-14	1.36***	0.02	0.71***	-0.50***
	(0.48)	(0.37)	(0.21)	(0.18)
Population share aged 15-24	1.44**	0.44	0.93***	-0.31
	(0.60)	(0.46)	(0.23)	(0.20)
Population share aged 25-34	-0.40	-0.29	0.11	-0.83***
	(0.57)	(0.45)	(0.24)	(0.24)
Population share aged 35-44	3.88***	1.53**	1.04***	0.30
	(1.01)	(0.62)	(0.32)	(0.32)
Population share aged 45-54	1.59	-0.78	0.69*	-0.74**
	(1.06)	(0.73)	(0.37)	(0.37)
Population share aged 55-65	1.97*	-0.09	1.52***	-0.88*
	(1.07)	(0.85)	(0.44)	(0.45)
Urbanization rate	0.17***	0.27***	-0.09***	0.10***
	(0.05)	(0.04)	(0.02)	(0.01)
Constant	-1.54***	-0.61	-0.20	0.50***
	(0.48)	(0.38)	(0.19)	(0.18)
Observations	539	539	539	539
R-squared	0.61	0.86	0.63	0.72

Robust standard errors clustered at the mesoregion level in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.9: Pre-trends tests

	1991-2000 shocks		2000-2010 shocks	
	Females	Males	Females	Males
	(1)	(2)	(3)	(4)
Panel A: Employment growth residuals				
Residuals of 1980-1991 female shocks	0.17			
	(0.28)			
Residuals of 1980-1991 male shocks		-0.15		
		(0.13)		
Residuals of 1991-2000 female shocks			1.93***	
			(0.45)	
Residuals of 1991-2000 male shocks				-0.71***
				(0.23)
Panel B: Wage growth residuals				
Residuals of 1980-1991 female shocks	0.06			
	(0.12)			
Residuals of 1980-1991 male shocks		0.10		
		(0.08)		
Residuals of 1991-2000 female shocks			-1.53***	
			(0.43)	
Residuals of 1991-2000 male shocks				-0.26
				(0.26)

Robust standard errors clustered at the mesoregion level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

C. Model solutions appendix

This appendix describes the solutions of the model in greater detail.

C.1. Equilibrium under autarky

In the solution under autarchy, regional population N_{jt} is assumed exogenous, and equilibrium is characterized by male labor, female labor, and housing markets clearing.

First I solve for for the gender employment and wage gaps. Note that Equations 6 and 7 together yield a supply-side gender gap expression:

$$\frac{W_{Mjt}}{W_{Wjt}} = \frac{1}{1+T_{jt}} \left(\frac{N_{Mjt}}{N_{Wjt}}\right)^{\frac{1}{\iota}} \tag{19}$$

Combining equations 19 and 3, I obtain:

$$\frac{N_{Mj}}{N_{Wj}} = \left[(1+T_{jt}) \left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\sigma}\right]^{\frac{\iota}{1-\iota(\beta\sigma-1)}} \tag{20}$$

$$\frac{W_{Mj}}{W_{Wj}} = \left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\frac{\sigma}{1-\iota(\beta\sigma-1)}} (1+T_{jt})^{\frac{\iota(\beta\sigma-1)}{1-\iota(\beta\sigma-1)}} \tag{21}$$

These expressions in turn allow me to write the gender-specific inverse labor demand in terms of own-gender employment and exogenous parameters. To do this, I take the aggregate effective labor used by firms in region j as:

$$L_{jt} = \left[\left(\psi_{W_{jt}} N_{Wjt}^{\beta}\right)^{\sigma} + \left(\psi_{M_{jt}} N_{Mjt}^{\beta}\right)^{\sigma}\right]^{\frac{1}{\sigma}} \tag{22}$$

which is a component of the production function (equation 1). Using 21 I can re-write 22 as

$$L_{jt} = N_{Wjt}^{\beta} \left[\psi_{W_{jt}}^{\sigma} + \psi_{M_{jt}}^{\sigma} \left[(1+T_{jt}) \left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\sigma}\right]^{\frac{\beta\iota\sigma}{1-\iota(\beta\sigma-1)}}\right]^{\frac{1}{\sigma}}, \text{ or} \tag{23}$$

$$L_{jt} = N_{Mj}^{\beta} \left[\psi_{W_{jt}}^{\sigma} \left[(1+T_{jt}) \left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\sigma}\right]^{\frac{\beta\iota\sigma}{\iota(\beta\sigma-1)-1}} + \psi_{M_{jt}}^{\sigma}\right]^{\frac{1}{\sigma}} \tag{24}$$

Labor market for females

Using equation 23, female labor demand can be expressed as:

$$W_{Wjt} = \lambda_1 \psi_{Wjt}^{\sigma} N_{Wjt}^{\xi_1} \Psi_{Wjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}} \tag{25}$$

where $\Psi_{Wjt} := \left[\psi_{W_{jt}}^{\sigma} + \psi_{M_{jt}}^{\sigma} \left[(1+T_t) \left(\frac{\psi_{Mjt}}{\psi_{Wjt}} \right)^{\sigma} \right]^{\frac{\beta\iota\sigma}{1-\iota(\beta\sigma-1)}} \right]^{\frac{1}{\sigma}}$, $\lambda_1 := \beta\gamma^{\frac{\gamma}{1-\gamma}} \bar{Z}^{\frac{1-\beta-\gamma}{1-\gamma}}$, and $\xi_1 := \frac{\beta\gamma(1-\sigma)+(1-\gamma)(\beta\sigma-1)}{(1-\gamma)}$.

Equating female labor demand in 25 and labor supply in 6 yields equilibrium employment and wages:

$$\begin{aligned} N_{Wjt}^{*aut} &= N_{jt}^{\frac{1}{1-\iota\xi_1}} \left(\frac{\lambda_1}{1+T_t} \right)^{\frac{\iota}{1-\iota\xi_1}} \psi_{Wjt}^{\frac{\iota\sigma}{1-\iota\xi_1}} \Psi_{Wjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)} \frac{\iota}{1-\iota\xi_1}} \\ W_{Wjt}^{*aut} &= N_{jt}^{\frac{\xi_1}{(1-\iota\xi_1)}} \left(\frac{\lambda_1}{1+T_t} \right)^{\frac{1}{1-\iota\xi_1}} \psi_{Wjt}^{\frac{\sigma}{1-\iota\xi_1}} \Psi_{Wjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)} \frac{1}{1-\iota\xi_1}} \end{aligned}$$

Labor market for males

Using equation 24, male labor demand can be written as:

$$W_{Mjt} = \lambda_1 \psi_{Mjt}^{\sigma} N_{Mjt}^{\xi_1} \Psi_{Mjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}} \tag{26}$$

where $\Psi_{Mjt} := \left[\psi_{W_{jt}}^{\sigma} \left[(1+T_t) \left(\frac{\psi_{Mjt}}{\psi_{Wjt}} \right)^{\sigma} \right]^{\frac{\beta\iota\sigma}{\iota(\beta\sigma-1)-1}} + \psi_{M_{jt}}^{\sigma} \right]^{\frac{1}{\sigma}}$.

Equilibrium employment and wages for men follow from equating labor demand in 26 and labor supply in 7:

$$\begin{aligned} N_{Mjt}^{*aut} &= N_{jt}^{\frac{1}{1-\iota\xi_1}} \lambda_1^{\frac{\iota}{1-\iota\xi_1}} \psi_{Mjt}^{\frac{\iota\sigma}{1-\iota\xi_1}} \Psi_{Mjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)} \frac{\iota}{1-\iota\xi_1}} \\ W_{Mjt}^{*aut} &= N_{jt}^{\frac{\xi_1}{(1-\iota\xi_1)}} \lambda_1^{\frac{1}{1-\iota\xi_1}} \psi_{Mjt}^{\frac{\sigma}{1-\iota\xi_1}} \Psi_{Mjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)} \frac{1}{1-\iota\xi_1}} \end{aligned}$$

Housing rents

Equation 9 can be re-written as:

$$R_{jt}^{*aut} = \left(\zeta \bar{W}_{jt}^{*aut} N_{jt} \right)^{\frac{1}{1+\rho}} \tag{27}$$

with $\zeta := \frac{\alpha}{\bar{H}\left(\frac{1+r_t}{r_t}\right)^{\rho}}$. The net wage under autarky is in turn defined by the wage and employment equilibria in equations 13, 15, 14 and 16, and the average labor force participation costs of male and women in the workforce. Specifically:

$$\bar{W}_{jt}^{*aut} = \left(\frac{N_{Wjt}^{*aut}}{N_{jt}} W_{Wjt}^{*aut} - \bar{\varphi}_{Wjt}\right) + \left(\frac{N_{Mjt}^{*aut}}{N_{jt}} W_{Mjt}^{*aut} - \bar{\varphi}_{Mjt}\right)$$

The average participation costs correspond to the expected value for the population of each gender for whom their wages are weakly larger than the costs. Given the functional form assumption on $F(\varphi_i)$, these are give by:

$$\bar{\varphi}_{Wjt} = \frac{\iota}{\iota+1}(1+T_{ij})\left(\left(\frac{W_{Wjt}^{aut*}}{1+T_{ij}}\right)^{\iota+1} - 1\right) \tag{28}$$

$$\bar{\varphi}_{Mjt} = \frac{\iota}{\iota+1}\left(\left(W_{Mjt}^{aut*}\right)^{\iota+1} - 1\right) \tag{29}$$

C.2. Equilibrium in the open region

When the region is open to labor migration, population becomes an endogenous variable. Under the spatial equilibrium assumption, migration arbitrages away household-level welfare differences across regions, such that household indirect utility equals the utility in the reservation region $\underline{U}$.

Spatial indifference curves and local population

Given the equilibrium rent equation in 9, the spatial indifference curve can be written as:

$$V_{jt}\left(\theta_j, \bar{W}_{jt}^{net}, N_{jt}\right) = \underline{\mathrm{U}} = \zeta_t \theta_j \left(E\left(\bar{W}_{jt}^{net}\right)\right)^{\frac{1+\rho-\alpha}{1+\rho}} N_{jt}^{-\frac{\alpha}{1+\rho}}$$

where the net household wage enters the utility function as an expectation because, before migration, there is uncertainty about the individuals' participation costs. It is defined as the sum of the expected wage of men and women, namely $E\left(\bar{W}_{jt}^{net}\right) = E\left(\bar{W}_{Mjt}^{net}\right) + E\left(\bar{W}_{Wjt}^{net}\right)$.

Households observe the distribution of labor force participation costs, and therefore know each of their members' probability of participating in city j given local wages, namely $\left(\frac{W_{Wjt}}{1+T_t}\right)^{\iota}$ for women and W_{Mjt}^{ι} for men, as well as the average costs of the people who participate from equations 28 and 29. Combining these equations yields an expression for the expected net labor income for men and women in city j:

$$E\left(W_{Wj}^{net}\right) = \left(\frac{W_{Wjt}}{1+T_t}\right)^{\iota}\left(W_{Wjt}-\frac{\iota\left(1+T_t\right)}{\iota+1}\left(\left(\frac{W_{Wjt}}{1+T_t}\right)^{\iota+1}-1\right)\right)$$

$$E\left(W_{Mj}^{net}\right) = W_{Mjt}^{\iota}\left(W_{Mjt}-\frac{\iota}{\iota+1}\left(W_{Mjt}^{\iota+1}-1\right)\right)$$

Equilibrium outcomes

The spatial indifference curve can also be written as an expression for the local population in terms of expected household wages (equation 10). Using this and the solutions for the equilibrium under autarky, one can obtain equations that implicitly define the endogenous variables of the model in terms of the exogenous parameters. This is turn can be used to perform comparative static analysis of the effects of shocks to male and female local labor demand.

Because I can express male wages as a function of female wages and viceversa using equation 21, I can write equations 11 and 12, and ultimately the population equation in 10 in terms of male wages (rather than in terms of expected net household wages):[23]

$$N_{jt} = \left(\frac{\zeta\theta_j}{\underline{\mathrm{U}}}\right)^{\frac{1+\rho}{\alpha}}\left[W_{Mjt}^{\iota}\left(W_{Mjt}\frac{\iota\left(1-W_{Mjt}^{1+\iota}\right)}{1+\iota}\right)+\left(\frac{\iota T_{Wt}\left(1-\Phi_{jt}^{1+\iota}\right)}{1+\iota}+T_{Wt}^{\iota_M}W_{Mjt}\left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\sigma_M}\right)\Phi_{jt}^{\iota}\right]^{\frac{1-\alpha+\rho}{\alpha}} \tag{30}$$

where $T_{Wt} := 1+T_t$, $\Phi_{jt} := T_{Wt}^{\iota_M-1}W_{Mjt}\left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\sigma_M}$, $\iota_M := \frac{\iota(\beta\sigma-1)}{\iota(\beta\sigma-1)-1}$, and $\sigma_M := \frac{\sigma}{\iota(\beta\sigma-1)-1}$.

Recall that the labor market solution under autarky expresses the male wage in terms of the population and exogenous parameters (equation 16). Replacing it into equation 30 yields and expression that implicitly defines the population in terms of the exogenous parameters of the model.

This equation in turn can be used to obtain the equilibrium housing rents in the open region. To see this, notice than in equation 9 the product of household net wages and housing rents can be written as $\bar{W}_{jt}^{*aut}N_{jt} = N_{Wjt}^{*aut}W_{Wjt}^{*aut}+N_{Mjt}^{*aut}W_{Mjt}^{*aut}-N_{jt}\left(\bar{\varphi}_{Wjt}+\bar{\varphi}_{Mjt}\right)$. This in turn allows me to express population in terms of rents and the autarky solutions for employment and rents:

$$N_{jt} = \frac{N_{Wjt}^{*aut}W_{Wjt}^{*aut}+N_{Mjt}^{*aut}W_{Mjt}^{*aut}-\frac{R_{jt}^{1+\rho}}{\zeta}}{\bar{\varphi}_{Wjt}+\bar{\varphi}_{Mjt}} \tag{31}$$

Replacing equation 31 and the autarky employment and wage solutions in equations 13 through 16 into the open-city population equation yields an expression that implicitly defines local housing

[23] I can alternatively express the population in terms of female wages and exogenous parameters, obtaining equivalent solutions. I use the male wage expression because it yields a more succinct expression.

rents in terms of the exogenous parameters of the model.

Using similar processes I obtain equations that implicitly define gender-specific wages and employment. I take the autarky equilibrium male wage in equation 16 and replace N_{jt} with expression 30, obtaining the equilibrium male wage in the open region. The employment solution involves two additional steps. First, I use the employment gap equilibrium under autarky in equation 20 and combine it with the labor demand equation in 2 to express male wages in terms of male employment and exogenous parameters. Second, I plug in the resulting equation in the expression for the open-region equilibrium male wage. An equivalent procedure allows me to obtain equilibrium wages and employment for females. I omit reporting the full expressions for the sake of space, but they are available upon request.

D. Data appendix

D.1. Databases Used

Acronym	Database	Years	Source
PC	IBGE - Population census microdata sample	1980 (10%) 1991 (5%).	IBGE microdata made available by the Centro de Estudos da Metrópole web.fflch.usp.br/centrodametropole
		2000 (5%) 2010 (5%)	IBGE microdata loja.ibge.gov.br/populacao/amostra
IPEA1	IPEA - Municipality areas	2010	www.ipeadata.gov.br
IPEA2	IPEA - Climate data	2002	www.ipeadata.gov.br
IBGE1	IBGE - Municipality Borders GIS files	2010	https://mapas.ibge.gov.br/bases-e-referenciais/bases-cartograficas/malhas-digitais.html
IBGE2	IBGE - Evolution of municipality borders over census years	1872-2010	www.ibge.gov.br/home/geociencias/geografia/default_evolucao.shtm
IBGE3	IBGE - National consumer price index	1980-2010 (montly)	ww2.ibge.gov.br/home/estatistica/indicadores/precos/inpc_ipca/default seriesHist.shtm

D.2. Individual-level variables definitions

Variable	Samples	Description / comments
Wage	PC 1980, 1991, 2000 and 2010; IBGE3.	Monthly labor income in main occupation in the reference period, in 2010 reais.* **
Log wage residual	PC 1980, 1991, 2000 and 2010.	Residuals of an individual-level regression of the log of wage on individual characteristics including age categories, schooling categories, sex and race. Regressions are restricted to the correspondent subpopulation (e.g. female wage residuals are estimated using only female workers observations). All regressions use sample weights provided in the IBGE microdata samples.
Formally employed	PC 1980.	Individual that worked over the period of reference as employee and contributed to social security, or was an employer.***
	PC 1980, 1991, 2000 and 2010.	Individual that worked over the period of reference with a signed work card or as civil-service employede, or was an employer.** ***
Informally employed	PC 1980.	Individual that worked over the period of reference as employee and did not contribute to social security, or was self-employed.
	PC 1980, 1991, 2000 and 2010.	Individual that worked over the period of reference as a private sector or domestic employee without a signed work card, or was self-employed.**
Employed	PC 1980, 1991, 2000 and 2010.	Individual either formally or informally employed.
Unemployed	PC 1980, 1991, 2000 and 2010.	Individual that declared that they looked for employment but were not employed over the period of reference.**
Migrant	PC 2000, 2010.	Individual that declares that its time of residence in their current municipality is less or equal to 10 years (numerical response in variable V0416 in 2000 and V0624 in 2010).****

Variable	Samples	Description / comments
High-school educated	PC 1980, 1991.	Individuals that completed at least high-school-equivalent education (2do grau, colegial o medio 2do ciclo) based on variables V523 and V524 in 1980, V0328 and V3241 in 1991.
	PC 2000.	Individuals that completed at least high-school-equivalent education (2do grau, antigo classico, cientifico, etc. completed) based on variables V0432 and V4300 in 2000.
	PC 2010.	Individuals that completed at least high-school-equivalent education education (regular or supletivo de ensino medio, antigo classico, cientifico, etc. completed) based on variables V0633 and V0634.
Rent	PC 1991, PC 2010, IBGE3.	Montly value of housing rent.*
Rent residual	PC 1991, PC 2010.	Residuals of an household-level regression of the log of rent on individual housing unit characteristic including number of rooms, number of bedrooms, dwelling type, walls' material, and water source. Regressions are restricted to households that pay positive rents All regressions use sample weights provided in the IBGE microdata samples.
Industry of employment	PC 1980, 1991, 2000 and 2010.	Industry code for employed workers (from Dix-Carneiro and Kovak 2017.)
Major industry of employment	PC 1980, 1991, 2000 and 2010.	Four major industries based on CNAE - Domiciliar definition (Agriculture, Manufacturing, Services and Government.)

* All monetary values are expressed in 2010 reais. Variables are converted from prior currencies to reais and deflated using the national consumer price index (INCP) provided by the IBGE. The original INPC deflators are adjusted to account for inconsistencies derived from a dual-currency period in 1994, following the method proposed by Corseuil and Foguel (2002).

** The reference period changed between the censuses up to 1991 (when it was defined as the prior 12 months before the survey) and the censuses of 2000 and after (when it was defined as the prior week before the survey.)

*** Civil service employees and employers are excluded from the computations of the regional-level aggregate labor-market variables.

**** In all microregion-level aggregates the migrant definition is adjusted, to the extent the data allows, in order to include only those who lived in a different microregion before migrating (i.e. the definition excludes migrants from a different municipality within the same microregion). This correction is based on variables V4250 in 2000 (which only provides region of residence 5 years earlier) and V6254 in 2010.

D.3. Region-level variables definitions

Variable	Samples	Description / comments
Main outcome variables		
Migrant population	PC 2000, 2010.	Total population of adult migrants.
Population	PC 1980, 1991, 2000 and 2010.	Total population calculated over all observations (including population of all ages, not only adults).
Average log rent residual	PC 1991, 2010.	Average of the log rent residual at the region level, for households reporting positive montly rent payments.

Variable	Samples	Description / comments
Average log wage residual	PC 1980, 1991, 2000 and 2010.	Average of the log of the wage residual at the region level, for adult individuals reporting positive wage.
Employment	PC 1980, 1991, 2000 and 2010.	Total employed adult population.
Non-participant population	PC 1980, 1991, 2000 and 2010.	Total adult population that is not in the labor force.
Wage gap	PC 1980, 1991, 2000 and 2010.	Average log wage for males minus average log wage for females at the microregion level.
Employment gap	PC 1980, 1991, 2000 and 2010.	Ratio between share of employed in adult males and share of employed in adult females.
Control Variables		
Log of population density	PC 1980, 1991, 2000 and 2010; IPEA1.	Log of the ratio Population / Area.
Average winter temperature	IPEA2	Average winter temperature (June-August) in celsius. Microregion-level variable is an area-weighted average of municipal-level measures.
Share of high-school educated	PC 1980, 1991, 2000 and 2010.	Share of high-school educated in adult population.
Formally-employed share in adults	PC 1980, 1991, 2000 and 2010.	Share of formally employed in adult population.
Informally-employed share in adults	PC 1980, 1991, 2000 and 2010.	Share of informally employed in adult population.
Unemploy-ment rate	PC 1980, 1991, 2000 and 2010.	Share of unemployed in the labor force.
Age group share (seven age groups)	PC 1980, 1991, 2000 and 2010.	Share of each age group in region's population age groups are defined as: 1) 0-14; 2) 15-24; 3) 25-34; 4) 35-44; 5) 45-54; 6) 55-64; 7) 65 or older. Group 7 is the omitted group in all regressions.
Urbanization rate	PC 1980.	Calculated from municipality aggregates published by the IBGE. In (IBGE2 source in subsection D.1).
	PC 1980, 1991, 2000 and 2010.	Share of total population living in locations classified as urban by the census (includes the urban districts of each municipality, as well as settlements that satisfy other geographic conditions (contiguitiy, infrastructure, and the availability of services.)
Major industry share in employment	PC 1980, 1991, 2000 and 2010.	Shared of major industry in regional employment.

Variable	Samples	Description / comments
Other variables (robustness and balance checks)		
Microregion	PC 1980, 1991, 2000, and 2010; IBGE2.	Time-consistent boundary of microregion. The definitions are constructed in two steps, following a procedure similar to that described in Kovak (2013). First, I construct time-consistent municipality boundaries (known in the literature as minimum-comparable areas - MCAs) by joining municipalities with common ancesters for the period 1980-2010, based on the official IBGE municipality family tree (see source IBGE2 in subsection D.1). IPEA provides a similar definition for the period 1872-2007 (Reis et al. 2007) but in this source MCAs are more aggregated than needed for accurate comparisons in recent decades. Second, I generate time-consistent microregions by aggregating MCAs that share common ancesters also for the period 1980-2010.
Microregion (robustness)	PC 1980, 1991, 2000 and 2010.	Time-consistent microregion from Dix-Carneiro and Kovak (2017), which in turn takes as an input the original MCAs definitions provided by IPEA (Reis et al. 2007).
Arranjos populacio-nais	PC 1980, 1991, 2000 and 2010.	Time-consistent Arranjos Populacionais (AP). Takes the original definition of AP (IBGE 2016) and joins arranjos that share a common MCA for the 1980-2010 period (using the same procedure as in the case of microregions).
Average log rent	PC 1991, PC 2010, IBGE3.	Montlhy rent paid. The average of the log rent (i.e. the geometric average) is calculated over all renter households in the region.
Average log wage	PC 1980, 1991, 2000 and 2010.	Average of the log wage (i.e. the geometric average) over employed adults with positive wage.
Non-employed share	PC 1980, 1991, 2000 and 2010.	Share of non-employed (non-participant or unemployed) in adult population.
Labor force	PC 1980, 1991, 2000 and 2010.	Adult population that is either formally employed, informally employed or unemployed.
Area (in square km)	IPEA1.	Geographic area in square kilometers, calculated aggregating the areas of the municipalities in each microregion.
Industry share in employment	PC 1980, 1991, 2000 and 2010.	Shared of industry in regional employment (used to compute the Bartik shocks).