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

Juan Pablo Chauvin

December, 2024

Abstract

Gender segmentation in the labor market is widespread. However, most existing studies of the effects of labor demand shocks on local economies ignore gender differences. 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 featuring gender-segmented labor markets and joint mobility frictions, which predicts that couples are more likely to migrate in response to male employment 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, with labor force participation being a relatively more important margin of adjustment. I find strong empirical support for the model's predictions in Brazil during 1991-2010. Comparing the effects of gender-specific labor demand shocks, I show that male-oriented shocks produce a higher migratory response and make localities more populated and expensive. These results imply that place-based policies creating jobs for women are more likely to benefit existing residents, while those creating male jobs are more likely to benefit immigrants and landlords.

JEL Codes: J16 O18 R13 R23 .

*I am grateful to Edward Glaeser and Melissa Dell for their guidance and support in this project. I also thank Sam Asher, Carlos Azzoni, Daniel Da Mata, Ricardo Hausmann, Stephan Heblich, Naercio Meneses Filho, Hildegunn Stokke, and multiple conference and seminar participants for useful comments and suggestions; as well as Brian Kovak and Christopher Poliquin for sharing data. Juan Nicolás Herrera provided outstanding research assistance. I gratefully acknowledge the support from the Harvard Center for International Development, the Weiss Family Fund for research in Development Economics, and the Harvard-Brazil Cities initiative from the David Rockefeller Center for Latin American Studies. All errors are my own. The opinions expressed in this publication are those of the authors and do not necessarily reflect the views of the Inter-American Development Bank, its board of directors, or the countries they represent.

1 Introduction

For decades, researchers and policymakers have been interested in 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, these differences exist, are large, and are likely to matter. Because men and women tend to segregate into different industries and occupations (Olivetti and Petrongolo, 2014), labor demand can disproportionately favor one gender depending on which industries are growing faster. Furthermore, because women are less likely than men to relocate away from their families (Sorenson and Dahl, 2016; Gemici, 2011; Costa and Kahn, 2000) and more likely to interrupt their careers when 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 new jobs favor male or female employment.

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

My model assumes that male and female workers are employed in different industries, each producing an intermediate good with its own productivity shifter subject to exogenous shocks. These intermediate goods are ultimately combined 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 equals or exceeds their exogenous labor force participation cost. I assume this cost is stochastic, with the distribution's support starting at a higher value for women than for men, reflecting extensive evidence that women face higher opportunity costs of labor force participation (Ponthieux and Meurs, 2015).

All individuals are married, with each female-male pair constituting 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 participation costs, females' contribution to household income will be smaller in expectation, and couples will be more likely to migrate in response to male rather than female work opportunities.

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

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 construct shift-share shocks by combining industry-level shares in local employment with gender-specific industry employment growth at the national level. These shocks predict what a region's gender-specific employment growth would have been if local industry shares had remained constant since 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 find strong empirical support for the prediction that households migrate more in response to male than female demand shocks. Male demand shocks increase the migrant population significantly more than female shocks. Joint mobility frictions appear to play an important role: women migrate more in response to male demand shocks than to shifts in their own labor demand, while men's 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, while female 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 suggest 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 following 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, while also highlighting the importance of other adjustment margins. *Male shocks* increase the population of both employed and non-employed *females*, consistent with male-led joint migration in which tied-migrant women find disproportionately fewer work opportunities. However, despite shifting female labor supply rightward, male shocks have a positive—though marginally significant—effect on local female wages. In the context of the model, this could be explained by large compensating differentials for housing rent increases. In practice, it could also be driven by family income effects on female labor supply or by changes in the skill composition of female labor, which the framework does not consider. In the aggregate, male demand shocks increase the employment and wage gender gaps in both the 1990s and 2000s, while female demand shocks reduce the gender employment gap but not the wage gap.

The asymmetric response of male and female labor markets to demand shocks translates into asymmetric welfare effects. While male-oriented local demand shocks are more likely to benefit immigrants and landlords, female-oriented 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 pressure on local housing prices, making workers more 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 increased 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 popular worldwide. My findings suggest that such policies can have substantially different effects depending on the gender composition of created jobs and the initial levels of male and female employment. Benefits to local populations can quickly dissipate through migration and higher local living costs if job creation predominantly favors men.

This paper contributes to several literatures. First, it relates to studies of labor demand shocks' effects 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 examines outcomes for the labor force as a whole or by skill group—aggregating male and female workers or restricting the analysis to males. Moreover, these works assume the marginal migrant is an individual. By introducing realistic yet tractable new assumptions—a joint location constraint for married couples and a higher opportunity cost of workforce participation for females—my paper shows that local labor demand shocks of equivalent size can lead to substantially different outcomes in population, rents, employment, and wages 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 focusing on the extent to which city migrants—rather than local resident—benefit from local demand shocks, which has produced contradictory results (Partridge et al., 2009; Bartik, 2004). My work shows that the gender composition of shocks can play an important role in determining both the workers-landlords and residents-migrants splits of welfare effects.

A closely related series of studies examines 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 likely affect labor demand differently for men and women because local exposure depends on the industry composition of places, and industries vary in their gender composition of employment. 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.

My work also contributes to the literature on 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 local labor and housing markets. Male-biased 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 depress female wages.

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

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

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

2 Spatial Equilibrium with Gender-Segmented Labor Markets

In this section, I develop a spatial equilibrium model that illustrates how gender-biased labor demand shocks affect local population, housing rents, and employment and wages for men and women. The model incorporates standard elements from the seminal Roback (1982) framework, where local wages, housing rents, and amenities determine workers' geographic sorting, and the marginal migrant's utility is equalized across space in equilibrium. This type of model has been extensively used in urban economics to study local labor demand shocks' effects in the U.S. and other high-income countries, but its use in less-developed countries has been limited (see Alves 2021, Morten and Oliveira 2024, and Oliveira and Pereda 2020 for recent applications in Brazil).[3] It offers significant advantages over partial equilibrium approaches by capturing how aggregate labor outcomes are shaped both by the shock's direct effects and by the endogenous adjustments of factor prices and quantities (Moretti, 2011).

I depart from the standard model by incorporating gender segmentation in the labor market and joint mobility constraints for married households.[4] In my model, the population consists of N married households indexed by i, each with two members, a woman (W) and a man (M). There are J regions indexed by j. Years are indexed by t. Each individual is endowed with one unit of labor. On the demand side, there are two industries producing intermediate goods, one employing male workers and the other female workers. These intermediate goods are ultimately combined as imperfect substitutes to produce a

[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 framework's adequacy in this context.

[4] The notion that joint mobility constraints can partly explain gender differences in labor market outcomes was 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.

nationally-traded good. Each industry has its own productivity shifter, which is subject to exogenous shocks.

To participate in the labor market, individuals incur a labor force participation cost φ_i, which is an exogenous stochastic variable with distribution $F(\varphi_i)$. This cost may reflect the opportunity cost of commuting (Black et al., 2014), childcare expenses (Baker et al., 2008; Paes de Barros et al., 2011), or the purchase of household appliances (Greenwood et al., 2005), among other factors. A key assumption of my model is that the distribution of this cost is gender-specific, with the support starting at a value that is higher for women than for men by T_t. This assumption reflects extensive evidence documenting higher opportunity costs of labor force participation for females (Ponthieux and Meurs, 2015). In this paper, I abstract from the specific mechanisms driving this difference and focus on its local labor market consequences.

Households observe local wages, housing rents, and amenities but learn their labor force participation costs only after choosing a location. However, they know $F(\varphi_i)$ in advance and, consequently, their expected labor income net of participation costs in each region. After choosing a location, individuals decide whether to enter the workforce or domestic production by comparing wage income with the cost of labor force participation. 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, each producing intermediate good Y_G for $G \in \{M, W\}$, where their labor is combined with traded capital K and non-traded capital $\bar{Z}_j$.[5] I assume that regions have many homogeneous firms, such that the region-level production function is identical to that of individual firms. The production function for the intermediate good is:

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

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

[5] Non-traded capital is added to the production function to allow for constant returns to scale at the firm level while maintaining decreasing returns to scale at the region level. Under these conditions, it is possible to have both a zero-profit condition for firms and a finite size of regions (Glaeser, 2008).

$$
\begin{aligned}
Y_{jt} &= \left(Y_{Wjt}^{\sigma}+Y_{Mjt}^{\sigma}\right)^{\frac{1}{\sigma}}, \text{ or} \\
Y_{jt} &= \left[\left(\psi_{W_{jt}}N_{Wjt}^{\beta}\right)^{\sigma}+\left(\psi_{M_{jt}}N_{Mjt}^{\beta}\right)^{\sigma}\right]^{\frac{1}{\sigma}} K_{jt}^{\gamma}\bar{Z}_{j}^{1-\beta-\gamma}\,. \qquad (2)
\end{aligned}
$$

I assume that $0 \leq \sigma \leq 1$, which implies that male and female effective labor are 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:

$$
\max_{N_{Mjt},N_{Wjt},K_{jt}}\left\{\left[\left(\psi_{W_{jt}}N_{Wjt}^{\beta}\right)^{\sigma}+\left(\psi_{M_{jt}}N_{Mjt}^{\beta}\right)^{\sigma}\right]^{\frac{1}{\sigma}} K_{jt}^{\gamma}\bar{Z}_{j}^{1-\beta-\gamma}-W_{Wjt}N_{Wjt}-W_{Mjt}N_{Mjt}-K_{jt}\right\}. \qquad (3)
$$

The solution yields the labor demand equations:

$$
\begin{aligned}
W_{Gjt} &= \beta\gamma^{\frac{\gamma}{1-\gamma}}\psi_{Gjt}^{\sigma}N_{Gjt}^{\beta\sigma-1}L_{jt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}}\bar{Z}_{j}^{\frac{1-\beta-\gamma}{1-\gamma}}\,, \qquad (4)\\
L_{jt} &= \left[\left(\psi_{W_{jt}}N_{Wjt}^{\beta}\right)^{\sigma}+\left(\psi_{M_{jt}}N_{Mjt}^{\beta}\right)^{\sigma}\right]^{\frac{1}{\sigma}}\,.
\end{aligned}
$$

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

$$
\frac{W_{Mjt}}{W_{Wjt}}=\left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\sigma}\left(\frac{N_{Mjt}}{N_{Wjt}}\right)^{\beta\sigma-1}. \qquad (5)
$$

Equation 5 shows that the local gender wage gap depends on the gender productivity difference, the degree of substitutability of male and female labor, and 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 ($\frac{\partial(W_{Mjt}/W_{Wjt})}{\partial\psi_{Mjt}}>0$), and negative in the case of females ($\frac{\partial(W_{Mjt}/W_{Wjt})}{\partial\psi_{Wjt}}<0$). 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 ($\frac{\partial(N_{Mjt}/N_{Wjt})}{\partial\psi_{Mjt}}>0$), they would also have a negative partial effect on the wage gap under the imperfect substitutes assumption ($0 \leq \sigma \leq 1$). Similarly, increases in female productivity could worsen the wage gap if female migration effects are large enough to outweigh the wage productivity premium.

2.2 Household Utility

Households choose locations to optimize a joint Cobb-Douglas utility function. As is standard in spatial equilibrium models following Roback (1982), they derive utility from the consumption of a composite tradable good C_{ijt} priced at one, housing rented at R_{jt},[6] and a local amenities index θ_j, which I assume to be exogenous and time-invariant for simplicity.[7] The household optimization problem is thus given by:

$$\max_{C_{ijt},H_{ijt}} \left\{\theta_j C_{ijt}^{1-\alpha} H_{ijt}^{\alpha}\right\} \quad \text{s.t.} \quad W_{ijt}^{net} = C_{ijt} + R_{jt}H_{ijt}\ , \tag{6}$$

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

$$W_{Gjt}^{net} = \begin{cases} W_{Gjt} - \varphi_{it} & \text{if the person sorts into the workforce} \\ 0 & \text{if the person does not.} \end{cases} \tag{7}$$

The optimized housing consumption is therefore:

$$H_{ijt}^{*} = \alpha \frac{W_{ijt}^{net}}{R_{jt}}\ . \tag{8}$$

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

$$V_{ijt}(\theta_j, W_{ijt}^{net}, R_{jt}) = \alpha^{\alpha}(1-\alpha)^{1-\alpha}\theta_j W_{ijt}^{net} R_{jt}^{-\alpha}\ . \tag{9}$$

The spatial equilibrium assumption implies that the indirect utility is equalized across space for the marginal household, $V_{ijt}(\theta_j, W_{ijt}^{net}, R_{jt}) = \underline{U}$. Note that restricting the choice to a single location entails that household utility may be smaller than in the standard spatial equilibrium framework, where individuals are able to choose 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 $\underline{U}_{ijt} \leq \underline{U}_M + \underline{U}_W$.

[6] For simplicity, I do not include home production or leisure in this version of the utility function. This helps to highlight the role of gender-asymmetric migration responses in the model, at the cost of assuming away income effects.

[7] 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 an 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:

$$W_{Wjt} = (1+T_t)\left(\frac{N_{Wjt}}{N_{jt}}\right)^{\frac{1}{\iota}} \ . \tag{10}$$

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

$$W_{Mjt} = \left(\frac{N_{Mjt}}{N_{jt}}\right)^{\frac{1}{\iota}} \ . \tag{11}$$

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:

$$\pi_{jt} = \sum_{t=0}^{\infty} \frac{R_{jt}}{(1+r_t)^t} - CC_{jt} \ , \tag{12}$$

where r_t is the national interest rate, and CC_{jt} are the local construction costs.[8] 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:

$$\bar{H}\left(\frac{1+r_t}{r_t}\right)^{\rho} R^{\rho}_{jt} \ . \tag{13}$$

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

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

time t. Based on equation 8, it can be written as:

$$H_{jt} = \alpha \frac{\bar{W}_{jt}^{net}}{R_{jt}} N_{jt} \,, \tag{14}$$
$$\bar{W}_{jt}^{net} = \left(\frac{N_{Mjt}}{N_{jt}} W_{Mjt} - \bar{\varphi}_{Mjt} \right) + \left(\frac{N_{Wjt}}{N_{jt}} W_{Wjt} - \bar{\varphi}_{Wjt} \right) \,.$$

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

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

$$R_{jt}^{*} = \left(\alpha \frac{\bar{W}_{jt}^{net}}{\bar{H}\left(\frac{1+r_t}{r_t}\right)^{\rho}} N_{jt} \right)^{\frac{1}{1+\rho}} \,. \tag{15}$$

2.5 Key Insights and Predictions

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

Equation 15 allows me to rewrite the indirect utility of households living in region j (equation 9) 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 across locations, $V_{jt}(\theta_j, E(W_{jt}^{net}), N_{jt}) = \underline{U}$. The spatial indifference curve can be used to express the local population in terms of the expected net household wage:

$$N_j = \left[E(W_{jt}^{net})\right]^{\frac{1+\rho-\alpha}{\alpha}} \left(\frac{\zeta \theta_j}{\underline{U}} \right)^{\frac{1+\rho}{\alpha}} \,, \tag{16}$$

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

$$E(W_{Wj}^{net}) = \left(\frac{W_{Wjt}}{1+T_t} \right)^{\iota} \left[W_{Wjt} - \frac{\iota(1+T_t)}{\iota+1} \left(\left(\frac{W_{Wjt}}{1+T_t} \right)^{\iota+1} - 1 \right) \right] \,, \tag{17}$$

$$E(W_{Mj}^{net}) = W_{Mjt}^{\iota} \left[W_{Mjt} - \frac{\iota}{\iota+1} \left(W_{Mjt}^{\iota+1} - 1 \right) \right] \,, \tag{18}$$

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 A for details).

2.5.1 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 of the female-intensive industry ($\Delta\psi_{Wjt}$) and the male-intensive industry ($\Delta\psi_{Mjt}$) in region j, which correspond to shifts in female and male local labor demand respectively. From the labor demand expression (equation 4), 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 17 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 18. 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 15), shocks to labor demand for males—compared to equivalent shocks for female labor—will also have a larger effect on housing rents.

2.5.2 Effects of Male and Female Shocks on Employment

The equilibrium under autarky, which treats the regions' population as exogenous, is useful to provide intuition for 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:

$$N^{*aut}_{Wjt} = N_{jt}^{\frac{1}{1-\iota\xi_1}} \left(\frac{\lambda_1}{1+T_t}\right)^{\frac{\iota}{1-\iota\xi_1}} \psi_{Wjt}^{\frac{\iota\sigma}{1-\iota\xi_1}} \Psi_{Wjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}\frac{\iota}{1-\iota\xi_1}}, \tag{19}$$

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

$$
N^{*aut}_{Mjt} = N_{jt}^{\frac{1}{1-\iota\xi_1}} \lambda_1^{\frac{\iota}{1-\iota\xi_1}} \psi_{Mjt}^{\frac{\iota\sigma}{1-\iota\xi_1}} \Psi_{Mjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)} \frac{\iota}{1-\iota\xi_1}} , \tag{20}
$$

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

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 A for details).

These equations show that the direct effect of shocks to own-gender labor demand on employment is positive for both men and women. The gender-specific industry productivity terms ψ_{Gjt} in equations 19 and 20 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 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 19, it does not have a similar effect in equation 20.[9]

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 act 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 disproportionately larger effect on female employment because of their larger effect on population N_{jt}.

2.5.3 Effects of Male and Female Shocks on Wages

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

$$
W^{*aut}_{Wjt} = N_{jt}^{\frac{\xi_1}{1-\iota\xi_1}} \left(\frac{\lambda_1}{1+T_t} \right)^{\frac{1}{1-\iota\xi_1}} \psi_{Wjt}^{\frac{\sigma}{1-\iota\xi_1}} \Psi_{Wjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)} \frac{1}{1-\iota\xi_1}} \tag{21}
$$

$$
W^{*aut}_{Mjt} = N_{jt}^{\frac{\xi_1}{1-\iota\xi_1}} \lambda_1^{\frac{1}{1-\iota\xi_1}} \psi_{Mjt}^{\frac{\sigma}{1-\iota\xi_1}} \Psi_{Mjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)} \frac{1}{1-\iota\xi_1}} \tag{22}
$$

[9] 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.

Without household migration, the direct effects 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 in the employment equation, although the relative role of the input substitution term is larger.[10] The population term enters the equations negatively ($\xi_1 < 0$).

If the region is open to migration, the inflow of immigrants shifts the labor supply rightward, 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 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 is 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 10 and 11), 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 key 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.

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

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 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 B. Appendix tables C1 and C2 present summary statistics of the main regional variables for the 1990s and the 2000s, respectively, and Appendix tables C3 and C4 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).

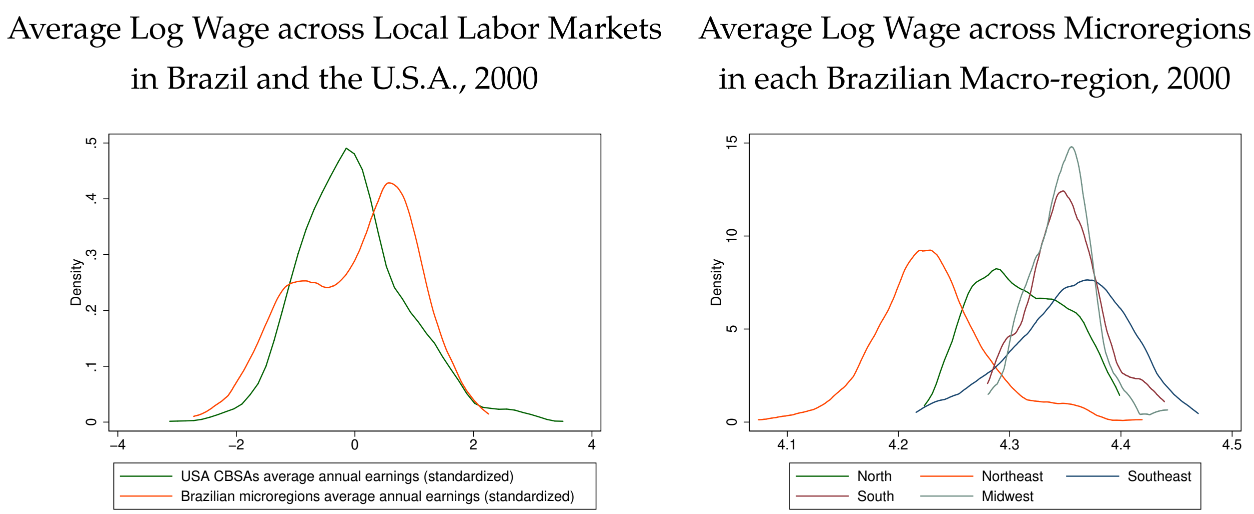
In order to be able to compare microregions across time, it is necessary to adjust for changes in administrative boundaries. The number of Brazilian municipalities grew dramatically over this period, going from 3,992 in 1980 to 4,491 in 1991 and to 5,565 in 2010. In a number of cases, the parent municipalities of newly created municipalities belonged to different microregions. I create time-consistent boundaries by aggregating the original IBGE microregions that share the same family tree over this period, as in Kovak (2013). The resulting sample includes 539 regions.[11] I use the microdata to generate regional-level aggregate measures for the different subsamples of interest (see Appendix B).

[11]The number of 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 recreate 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 B). 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.

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 U.S. (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 Northeast regions, and the richer South and Southeast 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 the average income of local labor markets in the U.S. follows a unimodal distribution, in Brazil the distribution is bimodal. The right panel shows that, underlying this unconventional shape, are large differences in labor income among the main geographic regions of the country.

Figure 1: Distribution of Labor Income across Local Labor Markets in Brazil and the U.S.A.



Inequality also has an important gender component, including a large gender wage gap and differences in labor force participation, work experience, and other correlates of labor productivity between men and women (Foguel, 2016). Part of these differences can be explained by women's historically limited access to formal education. Appendix table C5 shows that in 1991, the fraction of the population not participating in the labor force was twice as large among those with less than high-school education compared to those with a high-school diploma or higher education. But even among the more educated group, 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 C6 shows the distribution of labor force participation across local labor markets for the five Brazilian macro-regions by gender and education group.[12] Local labor markets in poorer areas tend to have lower participation rates than those in richer areas. These geographic differences are significantly less pronounced among the population with high-school education.

The country experienced very different macroeconomic performance across the two decades covered in this study. While 1990-2000 was characterized by volatility and rising unemployment, 2000 to 2010 saw consistent growth and improving economic opportunities, particularly for the lower-income population. The 1990s began with a sharp reduction in trade barriers and a major push for the privatization of state-owned enterprises. Hyperinflation, which had severely threatened the livelihood of millions of Brazilians during the 1980s and early 1990s, was halted in 1994 by a series of economic measures known as the "Plano Real," and a relatively stable period followed during the second half of the decade. This stability, however, was not enough to prevent massive job losses, and by the decade's end, unemployment had increased by 11 percentage points relative to 1991 levels (Table C5). In contrast, the 2000s saw significant GDP and employment growth, accompanied by progress in inequality reduction, 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).

Figure 2 illustrates the sharp differences between these two decades, showing national employment growth by industry and gender over these periods. Only a handful of industries avoided net job losses during the 1990s. Employment declined in primary industries, manufacturing, and services. Job losses did not systematically affect men or women across industries: while sectors like agriculture, textile manufacturing, and financial services saw disproportionate losses in male employment, female employment was more affected in sectors such as mineral mining, rubber product manufacturing, and utilities.

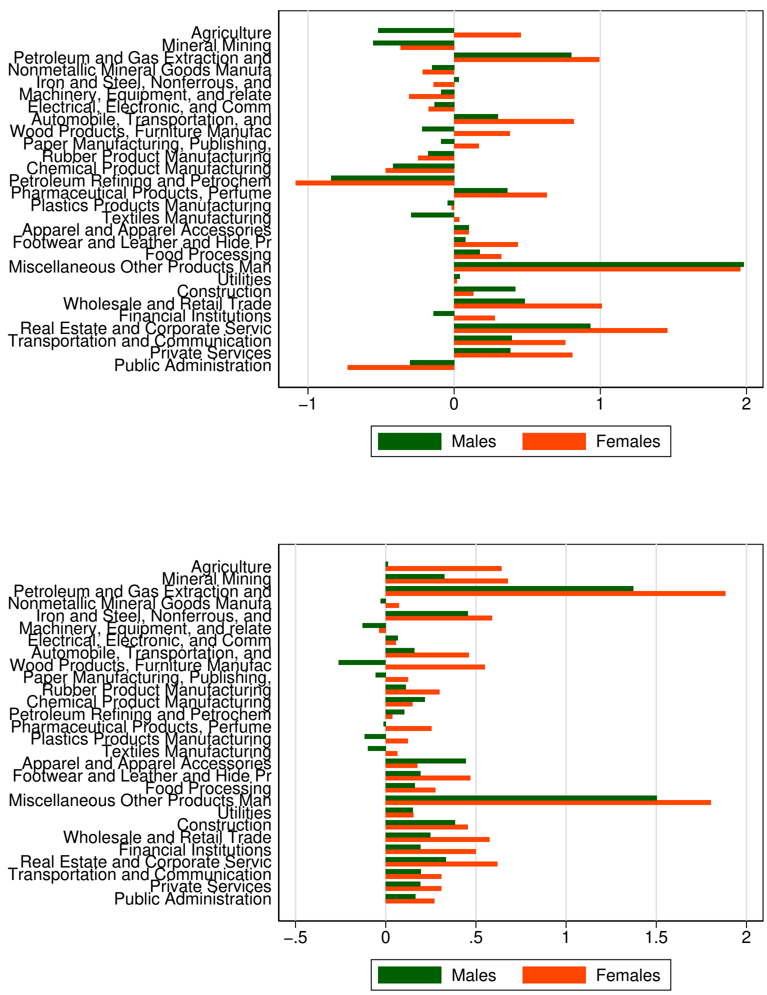
During the 2000s, in contrast, most industries grew. Females experienced larger proportional growth in most industries, partly reflecting lower initial employment levels. However, the relative growth of male and female jobs varied considerably across industries. My

[12] Macro-regions are the coarsest statistical division in the country, roughly equivalent to U.S. census regions.

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 about a reduction in internal migration. In the 2000 census, 17.41% of the population had been living in a different microregion ten years before. That number fell to 10.35% in the 2010 census. This reduction was driven by the subpopulation with lower levels of education (see Table C6 for details on internal mobility). In terms of the framework presented in Section 2, this implies that asymmetric migratory responses to male and female demand shocks likely played a less important role in determining local labor market outcomes in the 2000s than in the prior decade.

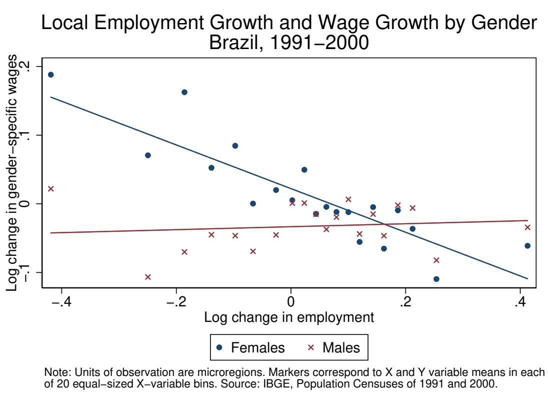
Figure 2: Employment Growth by Industry and Gender, Brazil 1991–2010



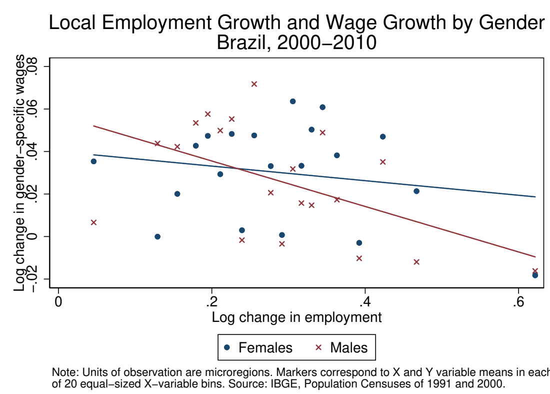
Differences in the relative role of migration may help explain the correlation between the gender wage gap and local employment growth at different points in time. The bin scatter plots in Figure 3 measure total employment growth (including males and females) on the horizontal axis and gender-specific 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 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 male wages 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 rose. 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

Average Log Wage across Local Labor Markets in Brazil and the U.S.A., 2000



Average Log Wage across Microregions in each Brazilian Macro-region, 2000



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 choose a single location and 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 used to empirically identify the effects of gender-specific changes in local labor demand on labor and housing markets. Specifically, I measure 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:

$$\Delta_{t-t_o} Outcome_j = \alpha + \beta_G \, \Delta_{t-t_o} Labor\ Demand_{jG} + \delta \, Controls_{j,t_0} + \Delta_{t-t_o} \epsilon_{jG} \tag{23}$$

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.

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 by 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:

$$Bartik^G_{jt} = \sum_{ind} \underbrace{\eta_{ind,j,t_0}}_{\substack{\text{Local industry} \\ \text{shares at } t_0}} \underbrace{\left(\log N^G_{ind,-j,t} - \log N^G_{ind,-j,t_0}\right)}_{\substack{\text{National change in gender } G \\ \text{industry employment}}} \tag{24}$$

where $N^G_{ind,-j,t}$ is the number of workers of subgroup $G \in \{M, W\}$ 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 inclusion of own-region employment may mechanically increase the predictive power of the shock. The gender-specific Bartik shocks in equation 24 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 C1 shows the distributions of male and female Bartik shocks for the two decades, and Figure C2 depicts the geographic distribution of these shocks.

Goldsmith-Pinkham et al. (2020) propose an econometric framework in which identification in Bartik-style shocks comes solely 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.

This implies that for the shock in equation 24 to produce causal estimates, the underlying identifying assumption is that the vector of industry shares is uncorrelated with the decade-long changes in the error term conditional on the set of controls. In their study, the authors assess this assumption empirically in the context of existing research that uses 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.[13] Additionally, they find evidence of pre-trends, even after accounting for the mechanical autocorrelation of the Bartik shocks over time, highlighting the importance of controlling for lagged growth.

To address these identification concerns, I implement two tests suggested by Goldsmith-Pinkham et al. (2020). First, I regress the gender-specific Bartik shocks on various start-year microregion characteristics and find strong correlations. The results, shown in Appendix Table C8, indicate that education levels (measured by the share of high-school educated adults in the population) are strong correlates of Bartik-style shocks in Brazil. They also reveal correlates that may be specific to lower-income contexts, such as urbanization rates and demographic structure—the shares of children and prime-age adults in the population exhibit strong connections with all shocks.

Second, I assess the presence of pre-trends that could bias the estimates. To avoid capturing mechanical trends arising from serial autocorrelation of the shocks,[14] the test

[13] 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.

[14] Amior and Manning (2015) show that serial correlation in demand shocks can explain large variations in local joblessness.

first obtains residuals from 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 this exercise using growth in wages as an outcome. If future shocks predict the fraction of lagged outcomes unexplained by contemporary shocks, this indicates the presence of pre-trends. The results of these tests, shown in Table C9, reveal no statistically significant evidence of pre-trends in the 1990s but strong evidence in the 2000s.

To address concerns raised by correlations with start-year variables and the presence of pre-trends, I include a set of base-year and lagged controls in all regressions. These controls are partially 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 (accounting for demographic differences across localities), urbanization rate, formal and informal employment shares in the population, unemployment rate, and winter temperatures as a proxy for climate amenities.[15] The lagged-growth controls include changes in the decade preceding the start year for population, wages, informal and formal employment, unemployment, and urbanization rates. My preferred specification also includes controls to prevent comparing structurally dissimilar local economies: employment shares in three broadly defined industries (agriculture, manufacturing, and government) and state fixed effects. Therefore, my results reflect comparisons of microregions within states that have broadly similar industry structures.

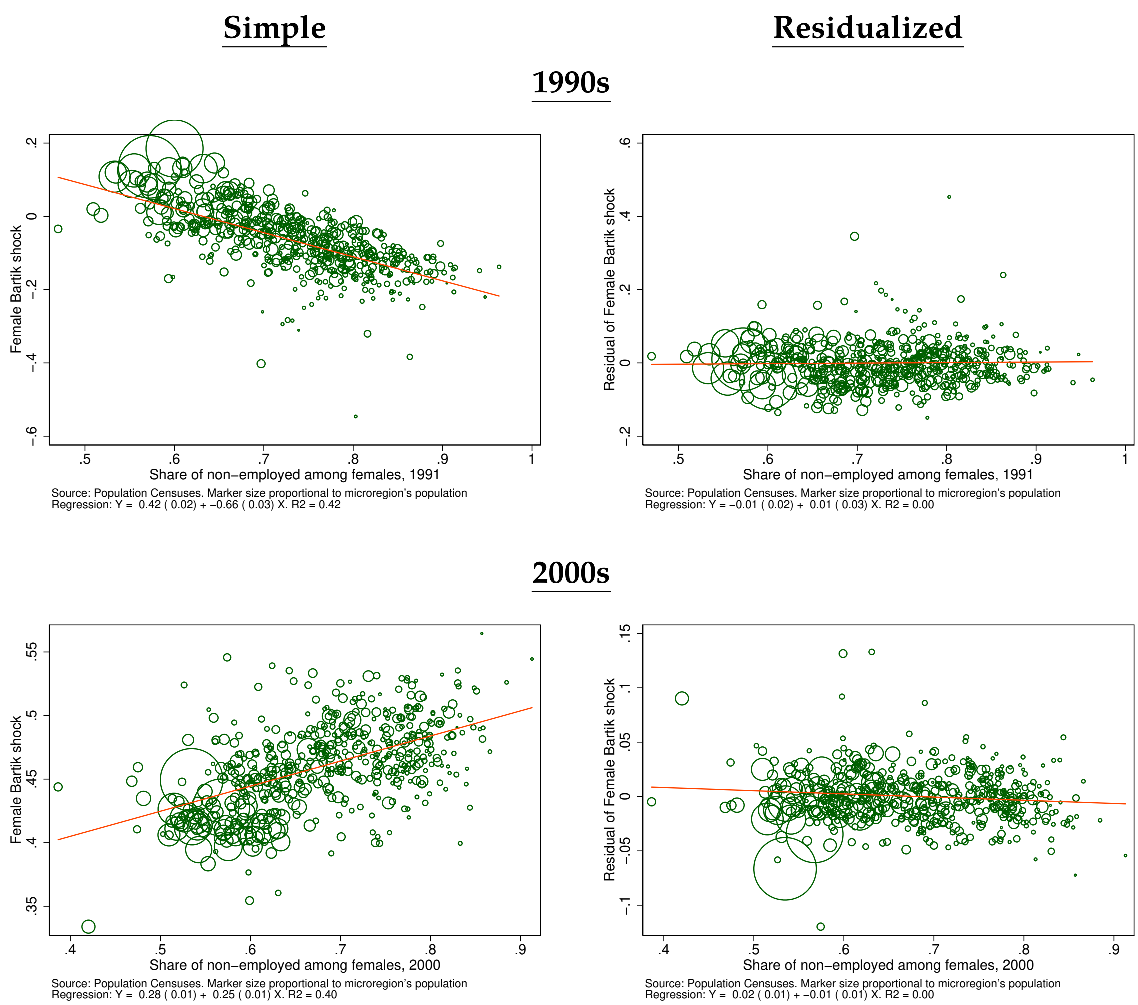
The coefficients on the gender-specific Bartik shocks can be given a causal interpretation under the selection-on-observables assumption. While one cannot definitively rule out potential unobservable confounders, examining correlations with regional characteristics not included in the control set can be informative. If the shocks remain correlated with other start-year or lagged variables after controlling for the variables described above, this would challenge identification. I perform this exercise with multiple variables and find that the remaining variation in the shock is uncorrelated with characteristics not included as controls.

Figure 4 presents an example of these tests. I compare the Bartik shocks before and after controls with the share of non-employed individuals (i.e., non-participants or un-

[15]Temperature appears to be a good proxy for time-invariant amenities affecting location decisions in Brazil. Oliveira and Pereda (2020) 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 higher in places with better climate amenities.

employed) in the adult female population for both decades. The left column shows the Bartik shock measures without modifications, while the right column shows the residuals from regressions of the shocks on the controls. The evidence suggests that the included variables effectively control for other potential confounders.[16]

Figure 4: Female Bartik Shocks and Base Year Female Non-participation



Source: Own calculations using census data.

[16]In this case, as in most cases tested, using only a small set of controls (population density, wages, education, informality, and urbanization rates) is sufficient to eliminate the correlation with non-included controls.

4 Results

This section presents the empirical results of the paper. I estimate reduced-form regressions as described in equation 23, using decade-long changes for the 1990s and 2000s. The units of observation are Brazilian microregions, and I use gender-specific Bartik shocks to capture exogenous shifts in male and female labor demand.

I examine five key aspects of the relationship between gender-specific labor demand and local outcomes. First, I analyze the migration elasticity of households with respect to male and female labor demand shocks, establishing 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 living costs. Third, I evaluate the effects of gender-specific labor demand shocks on employment, finding that male shocks tend to increase the employment gender gap while female shocks decrease it. Fourth, I examine the net effect of gender-specific shocks on wages, finding that male shocks worsened the wage gap in both decades, while female shocks also worsened it during the 1990s. Finally, I analyze the effects on the non-participating population by gender. Male shocks reduce the non-participating male population while increasing the non-participating female population. Conversely, female shocks either fail to reduce or even increase the non-participating female population.

The analysis focuses on adults aged 15 through 64 who are not enrolled as students in educational institutions. My preferred specification excludes groups whose wage determination likely follows different logic from standard market forces, including employers, career public servants, and members of security forces. Robustness checks that relax these restrictions preserve all key results. All regressions include the set of controls described in Section 4 and cluster 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 examining the effects of gender-specific labor demand shocks on male and female migration. Table 1 presents coefficients from the regression model described in equation 23. The outcome variable is the log population of each subgroup that reported living in a different microregion at the beginning of the decade (census year $t - 10$) compared to the end of the decade (census year t).

Columns 1 and 2 show the effects of female and male shocks on own-gender migration, while columns 3 and 4 report the effects of other-gender shocks (male shocks on female migration and female shocks on male migration, respectively). The final four columns present test statistics and p-values from Wald chi-square tests of the null hypothesis that corresponding male and female coefficients are equal, based on seemingly unrelated regression models including the correspondent female and male regressions. The difference being tested is indicated in each column's title (for example, figures in the fifth column test the difference between coefficients in columns 1 and 2). For each outcome, I calculate effects separately for two education subgroups: adults with a high-school degree or higher, and adults without a high-school degree. This analysis helps assess whether aggregate gender effects might be influenced by within-gender human capital heterogeneity.[17] Unless otherwise specified, tables for other outcomes follow this 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

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

The results strongly support two key hypotheses: couples tend to migrate together, and they are more likely to migrate in response to changes in male labor demand. Three findings support these conclusions. First, the effect of male Bartik shocks on own-gender migration significantly exceeds the equivalent effect of female shocks in both decades, although the

[17]Note that the population without a high-school degree represents a significant majority of employees during this period, and variation in the Bartik shocks is disproportionately driven by variation in employment opportunities for this subpopulation.

2000s results show less precision, consistent with lower aggregate migration in that decade. Second, male shocks exhibit larger effects on other-gender migration compared to female shocks. Third, the magnitude of migrant population response for both 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 was more pronounced at younger ages, strongest between ages 15 and 34 (see Appendix Figure C3). Moreover, the disproportionately larger responses of females to male shocks were much smaller and statistically insignificant in the 2000s, when migration declined across the country. This suggests that the migration mechanisms highlighted in Section 2 were more prevalent in the 1990s, a consideration important for interpreting the subsequent results.

The composition of the migrant population supports both the joint mobility assumption and the asymmetric response to male and female shocks. Table C6 shows that while 57% of the adult population is married, this share rises to 62% among migrant adults.[18] Among those with less than high-school education, the married share is 69% in the aggregate population and 71% among migrants.

If females typically stayed behind during Brazilian internal economic migration, we would expect to observe a disproportionately high share of males in the migrant population, particularly among married migrants. However, Table C6 shows that females actually comprise a larger share of the married migrant population. Males represent a larger share only among single migrants. The fact that women migrated more than men despite having relatively smaller own-gender migration elasticity suggests both that couples tend to move together and that they disproportionately follow male work opportunities.

Furthermore, evidence suggests that females migrated more than males despite, rather than because of, their employment prospects. Appendix Table C7 reports economic outcomes separately for migrants and the general population by gender and educational attainment in 2000. While migrant women show labor force participation and employment rates similar to population averages, migrant men exhibit lower non-participation and higher employment rates than regional averages. Less-educated migrant women participate more in the labor force than average but face higher unemployment rates. Highly-educated

[18] An important caveat when comparing married and single populations is that the census only provides contemporaneous information on marital status, not status at the beginning of the period. Marital status is likely endogenous to labor market shocks, as individuals' economic situations tend to affect their propensity to marry.

migrant women show lower labor force participation than average while still experiencing higher unemployment rates. In contrast, migrant men in both educational categories participate more and have lower unemployment rates than average. Additionally, migrant men are disproportionately employed in the formal sector, while migrant women are disproportionately employed in the informal sector.

4.2 Effects on population and housing rents

The gender asymmetries persist when examining log changes in population as the dependent variable (Table 2). A ten percent predicted increase in male employment was associated with a 7.1 percent increase in male population in the 1990s and a 7.6 percent increase in the 2000s. In contrast, a ten percent predicted increase in female employment corresponded to statistically insignificant increases of 2.9 percent in the 1990s and 0.9 percent in the 2000s. Migration responses appear to have been an important mechanism of adjustment to geographically heterogeneous demand changes, particularly during 1991-2000. This finding contrasts with Dix-carneiro and Kovak (2016), who find little evidence of interregional migration in Brazil in response to trade liberalization shocks, but aligns with Morten and Oliveira (2024), who document 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

Notes: Outcomes measured for individuals aged 15 through 64, excluding students, employers, civil servants, and public security personnel. All regressions include a constant. Robust standard errors clustered at the mesoregion level in parentheses, except for hypothesis tests. The hypothesis tests are Wald chi-square tests of the form $H_0 : \beta_{\text{males}} - \beta_{\text{females}} = 0$ 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 reveal potential composition effects. Despite women's lower migratory response, the population of females with high-school education or higher grew significantly in response to female labor demand shocks. Several factors contributed to significant growth in female labor force participation during this period, including increased female education, reduced family size, and faster urbanization rates (Scorzafave and Menezes-Filho, 2005). The coefficients by education group in column 1 of Table 2 suggest two possible explanations: either females endogenously acquired more education in localities with better female labor prospects, or following negative local employment shocks, the departing female population (whether following their husbands or seeking better opportunities) was disproportionately less educated, resulting in positive selection of the remaining female workforce. While my model considers worker heterogeneity only by gender, not skills, the interaction between education and gender in the context of local labor markets and joint mobility frictions presents 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 (1)	Female Shock (2)	Male Shock (3)	*Diff. Test* (χ^2 *and p-val.*) (4)
0.41	0.01	0.63**	*4.25*
(0.31)	(0.27)	(0.31)	*0.04*

Notes: Outcomes measured for individuals aged 15 through 64, excluding students, employers, civil servants, and public security personnel. All regressions include a constant. Robust standard errors clustered at the mesoregion level in parentheses, except for hypothesis tests. The hypothesis tests are Wald chi-square tests of the form $H_0 : \beta_{\text{males}} - \beta_{\text{females}} = 0$ on SUR models including the respective female and male regressions. *** 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 they should also have a larger effect on housing demand and, ultimately, housing rents. Table 3 reports these results. Housing rents are observed only in the 1991 and 2010 censuses, so the coefficients correspond to regressions on differences over a 20-year period (rather than the decade-long changes in other tables). The dependent variable is the change in average log rent controlling for dwelling characteristics. I run individual regressions of log housing rent on a vector of property characteristics (see Appendix B), obtain the residuals, and average them at the microregion level to obtain regional housing rents for each period.[19]

The results show that while male shocks had significant, positive, and large effects on housing rents, the effects of female shocks were indistinguishable from zero. A ten percent expected increase in male employment was associated with a 6.3 percent increase in housing rents. Relative to female labor demand shocks, male shocks made Brazilian regions more expensive over this period.

4.3 Employment effects

I now examine the effects on employment. 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, even without migration effects, because female employment is constrained by higher labor force participation costs. The model also predicts that the effects of other-gender shocks should be positive and larger for males.

The data generally support the model's employment predictions, as shown in 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, with effects driven by the low-education population. In contrast, a 10 percent increase in predicted female employment leads to a 6.9 percent increase in actual employment in the 1990s and a statistically insignificant 3.2 percent increase in the 2000s, with effects concentrated among those with a high-school degree or higher.

One deviation from the model's predictions is the observed negative effect of female shocks on male employment in the 2000s, concentrated in the low-education population. In the context of low migratory responses, this effect is determined by input substitution in production according to the theory. The negative coefficient suggests that low-education male labor may have been complementary to high-education female labor during this pe-

[19] All monetary variables in this paper are expressed in 2010 Reais, using INPC deflators published by 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

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

riod. The U.S. labor force polarization literature 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 abstracts from skills heterogeneity.

As shown in Table 5, the gender employment gap widened in response to male-leaning local demand shocks and narrowed in response to female-leaning shocks during the analysis period. The table directly measures the effects of shocks on the log differences across decades in the gap, defined as the ratio of male to female employment rates. These effects are predominantly 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 through different mechanisms. Appendix Figure C4 shows the predictive margins at different shock levels—that is, the predicted effects on the gap if all microregions had experienced the same shock intensity while maintaining their other characteristics. Male shocks tend to reduce employment gaps only at lower intensities; shocks above median intensity show no apparent effect on the gap. Conversely, female shocks' negative effects on the employment gap are concentrated at higher intensities, with the gap showing 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*

Notes: Outcomes measured for individuals aged 15 through 64, excluding students, employers, civil servants, and public security personnel. All regressions include a constant. Robust standard errors clustered at the mesoregion level in parentheses, except for hypothesis tests. The hypothesis tests are Wald chi-square tests of the form $H_0 : \beta_{\text{males}} - \beta_{\text{females}} = 0$ 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 now examine the effects of gender-specific local demand shocks on wages and labor force participation. In the context of the model, these outcomes are closely related: wages serve as the key endogenous driver of labor force participation decisions, while participation is also affected by its exogenously determined opportunity cost.

My preferred wage measure controls for observable individual characteristics including education levels, age (as a proxy for 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 average these wage residuals at the regional level for each subpopulation of interest. This approach is standard in the urban literature (e.g., Chauvin et al. 2017; Glaeser and Gottlieb 2009).

Table 6 shows that local male wages increase more than local female wages in response to equivalent demand shocks. In the aggregate sample, which combines both education groups, the effect of own-gender shocks on female wages is not statistically significant, while the corresponding effect on male wages is significant. The gender difference is statistically significant only in the 1990s, when migration effects were more pronounced.

The simultaneous occurrence of larger employment and wage effects from male shocks compared to female shocks is difficult to explain in a partial equilibrium framework. Larger employment effects typically suggest a more elastic labor supply curve, which should imply smaller wage effects. However, in general equilibrium, male shocks could generate larger wage and employment effects than female shocks due to substantial compensating

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

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

differentials for local living costs. This interpretation is consistent with the observation that housing rents respond to changes in male labor demand but not to female demand.

The combined wages and participation effects, however, cannot be fully accounted for by the assumptions of the model. Male shocks led to substantial immigration of both males and females, which should have generated downward pressure on female wages. One potential explanation within the model's framework is again compensating differentials, as increases in male labor demand raise regional costs for both household members. However, this explanation conflicts with the observed increase in the female non-participant population in response to male shocks, particularly during the 1990s (Table 7). According to the model, higher wages should have increased participation.

Understanding these results requires moving beyond the model's assumptions. One explanation involves income effects. The added worker effect—whereby married females reduce their labor force participation in response to increased wages or employment of married men—is well-documented in the literature at the individual level (Fernandes and de Felicio, 2005; Soares and Izaki, 2002). This effect could explain both reduced participation rates and increased female wages through backward shifts in female labor supply.

Alternative explanations involve skill composition effects. As suggested by the population results in Table 2, women may have endogenously sorted into education in regions with higher female labor demand, driving up female wages. If the added-worker effect

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

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

was more prevalent among the less-educated population, the remaining female workforce would be positively selected (Olivetti and Petrongolo, 2008). For instance, Hunt (2002) found that while the average wage gap in East Germany fell significantly following reunification, this change was largely explained by involuntary labor force exit among low-skilled workers, who were disproportionately women.

Including education as an additional dimension of heterogeneity makes the effects of shocks on participation and wages potentially non-monotonic. While workers with similar education levels might be imperfect substitutes, high- and low-education workers could be complements (Moretti, 2004). If skilled female workers complement unskilled male workers in production, increased demand for the former would raise wages and participation among low-skilled males, as observed in 1990s Brazil. These complementarities could explain why female labor demand shocks affect the gender wage gap differently across decades (Table 8) and why the predictive margins of these effects are non-linear and non-monotonic (as shown in Appendix Figure C5). Further research is needed to understand how gender and education differences interact in shaping local labor market outcomes.

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.*)
Panel A: 1991-2000	(1)	(2)	(3)	(4)	(5)	(6)
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*

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

4.5 Robustness

I perform multiple robustness checks examining the sensitivity of results to sample restrictions, definitions of local labor markets and industries, and the inclusion of different control variables.

Results may be sensitive to labor market definitions, particularly due to spatial autocorrelation. Geographically proximate regions may exhibit similar results, or outcomes may spill over to neighboring markets. While clustering standard errors at the mesoregion level addresses concerns about geographic correlation of shocks, it does not account for spillover effects. Using the minimum comparable microregions definition from Dix-carneiro and Kovak (2016), which involves a coarser aggregation of municipalities (411 microregions versus 539 in my sample), yields less precise but statistically significant results that support all previously discussed findings.

My main specifications include all Brazilian regions in unweighted region-level regressions, implying that relatively small, often less urbanized regions drive the results. To assess whether findings hold in large urban centers, I replicate the analysis using "Arranjos Populacionais" (IBGE, 2016)—groupings of core urban centers with closely integrated municipalities based on daily work and education commuting patterns. I consider both urban agglomerations and self-standing municipalities with large urban populations, applying the same correction for changing administrative boundaries described in Section 3.3. Most key results persist in this urban centers sample. Notably, female non-employment also decreases in the 1990s following male demand shocks, though this reduction remains significantly smaller than the decrease in male non-employment. This aligns with the view that local employment shocks in urban centers are less distortionary, as tied-migrant females are more likely to find employment in denser agglomerations.

I also check that the industry definition choice does not significantly affect results. Using industry definitions from Dix-carneiro and Kovak (2016), I find that Bartik shocks are highly correlated with those calculated using census definitions, and regression results remain unchanged across main specifications.

Sample restrictions also appear inconsequential. The main conclusions hold when the sample is limited to adults aged 25 to 64 (excluding the population aged 15-24), or when self-employed, government workers, and domestic workers are included.

The results generally remain robust to adding or removing plausibly relevant controls beyond the core baseline controls (initial income levels, age structure, urbanization rate, and share of high-school educated population). One exception occurs when controlling for base year share of non-employed men and women: the wage effect discrepancy loses statistical significance. However, differences in employment, population, and non-employment effects persist, with female non-employment effects remaining unambiguously positive and statistically significant. Consistent with theory, low labor force participation among local residents appears to drive part of the wage effects. Nevertheless, in aggregate, local male labor supply remains more elastic than female labor supply due to higher male migration elasticity.

4.6 Welfare and Policy Implications

The results discussed above imply that male and female labor demand shocks can have very different welfare consequences. When local female labor demand increases, firms can typically access a readily available regional labor pool, leading to higher employment among incumbent residents. In this context, local residents capture a larger share of the economic rents generated by the shock compared to outside workers and potential migrants. Because female immigration effects are more modest than male effects, pressure on housing prices remains limited. As discussed by Moretti (2011), when housing prices see limited increases, workers are likely to receive a larger fraction of benefits than landlords.

The evidence also suggests that female labor may be less efficiently allocated across space than male labor. This implies that local labor demand shocks for women could generate aggregate efficiency gains for the national economy by reducing misallocation – a promising area for future research.

The welfare consequences of male labor demand shocks differ substantially. Increases in local male labor demand generate larger migratory responses. The framework suggests that in these situations, local workers likely share larger fractions of economic rents with migrant workers and landlords.

These patterns have important implications for policy, particularly regarding regional development. Regional development policies, which typically aim to generate local employment in underdeveloped regions, are widespread globally (Kline and Moretti, 2014b) and have been used in Brazil since at least the 1940s (Resende, 2013; Cavalcanti Ferreira, 2004). My findings suggest that similar policies can have different effects depending on whether job growth favors male or female employment. Policies favoring male job creation over female job creation may see benefits to local residents dissipate through migration and higher local living costs. Moreover, initial employment rates by gender are likely matter: "place-making" policies may prove more effective at improving local economic conditions in areas with lower levels of female employment.

5 Conclusions

This paper demonstrates that local labor demand shocks can have significantly different effects by gender. Comparing shifts in local labor demand for males and females in Brazil during 1991-2010, I find that male-leaning employment shocks, relative to equivalent female-leaning shocks, generate larger increases in population, rents, and the gender economic gap.

I interpret these results through a spatial equilibrium model with gender-segmented labor markets. In this framework, gender differences in population and employment effects stem from joint mobility constraints of married couples. Since men typically face lower opportunity costs of labor force participation than women, male job prospects carry greater weight in household location decisions than female prospects. Consequently, household migration elasticity is larger with respect to male than female demand shocks, leading to larger effects on local population and prices. Through tied migration, shocks in labor demand of one gender affect the local labor supply of the other gender, with male shocks generating larger effects.

The empirical results largely support this mechanism. Additional adjustment margins appear to include composition effects—related to increasing female education and labor supply over time—and income effects—whereby individuals reduce labor supply as their partners' work conditions improve. These areas warrant further research.

Gender-differentiated migratory adjustments have important welfare implications. Because male employment shocks place greater pressure on housing rents than equivalent female shocks, male wage effects partly reflect compensating differentials for higher living costs. Consequently, male shocks tend to benefit migrants and landlords while exacerbating gender economic gaps, while female shocks more likely benefit local residents and reduce gender economic inequalities. Moreover, tied migration may lead to geographic misallocation of female labor, as tied-migrant women locate in suboptimal regions, and tied-stayer women underutilize job opportunities outside their residence compared to men.

These findings have significant policy implications. Regional development and other "place-making" policies can yield vastly different outcomes depending on their effects on gender-specific labor demand. In contexts with substantial gender and geographic disparities, like Brazil during the study period, this research points to significant advantages to expanding local female job opportunities.

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016). Import Competition and the Great US Employment Sag of the 2000s. *Journal of Labor Economics*, 34(S1):S141–S198.

Acemoglu, D., Autor, D., and Lyle, D. (2004). Midcentury Women, War, and Wages: The Effect of Female Labor Supply on the Wage Structure at Midcentury. *Journal of Political Economy*, 112(3):497–551.

Adão, R. (2015). Worker Heterogeneity, Wage Inequality, and International Trade: Theory and Evidence from Brazil.

Aizer, A. (2010). The Gender Wage Gap and Domestic Violence. *The American economic review*, 100(4):1847–1859.

Albouy, D. and Stuart, B. (2017). Urban Population and Amenities: The Neoclassical Model of Location.

Albrecht, J., Björklund, A., and Vroman, S. (2003). Is There a Glass Ceiling in Sweden? *Journal of Labor Economics*, 21(1):145–177.

Altonji, J. G. and Blank, R. M. (1999). Race and gender in the labor market. *Handbook of Labor Economics*, 3(3):3143–3259.

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

Amior, M. and Manning, A. (2015). The Persistence of Local Joblessness.

Autor, D. H. and Dorn, D. (2013). The Growth of Low Skill Service Jobs and the Polarization of the U . S . Labor Market. *American Economic Review*, 103(5):1553–97.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review*, 103:2121–2168.

Autor, D. H. and Duggan, M. G. (2003). The Rise in the Disability Rolls and the Decline in Unemployment. *Quarterly Journal of Economics*, 118(1):157–206.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2009). The Polarization of the U.S. Labor Market. *The American Economic Review*, 96(2):189–194.

Baker, M., Gruber, J., and Milligan, K. (2008). Universal Childcare, Maternal Labor Supply, and Family Well-Being. *Journal of Political Economy*, 116(4):709–745.

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

Bartik, T. J. (2004). Evaluating the Impacts of Local Economic Development Policies on Local Economic Outcomes: What has been done and what is doable? In *Evaluating local economic and employment development: how to assess what works among programmes and policies*, chapter 4, pages 113–142. OECD Publishing, Paris.

Bartik, T. J. (2015). How Effects of Local Labor Demand Shocks Vary with the Initial Local Unemployment Rate. *Growth and Change*, 46(4):529–557.

Beaudry, P., Green, D. a., and Sand, B. M. (2014). Spatial equilibrium with unemployment and wage bargaining: Theory and estimation. *Journal of Urban Economics*, 79:2–19.

Bertrand, M., Goldin, C., and Katz, L. F. (2010). Dynamics of the gender gap for young professionals in the financial and corporate sectors. *American Economic Journal: Applied Economics*, 2(3):228–255.

Bertrand, M., Kamenica, E., and Pan, J. (2015). Gender Identity and Relative Income Within Households. *The Quarterly Journal of Economics*, 130(2):571–614.

Black, D. A., Kolesnikova, N., and Taylor, L. J. (2014). Why do so few women work in New York (and so many in Minneapolis)?? Labor supply of married women across US cities. *Journal of Urban Economics*, 79:59–71.

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

Blau, F. D. (2016). *Gender, Inequality, and Wages*. Oxford University Press.

Blau, F. D. and Kahn, L. M. (2000). Gender Differences in Pay. *Journal of Economic Perspectives*, 14(4):75–100.

Blau, F. D. and Kahn, L. M. (2003). Understanding International Differences in the Gender Pay Gap. 21(1).

Busso, M., Gregory, J., Kline, P., and Berkeley, U. C. (2013). Assessing the Incidence and Efficiency of a Prominent Place Based Policy. *American Economic Review*, 103(2):897–947.

Carneiro, R. D. and Kovak, B. K. (2015). Trade liberalization and the skill premium: A local labor markets approach. In *American Economic Review*, volume 105, pages 551–557.

Cavalcanti Ferreira, P. (2004). Regional Policy in Brazil : A Review. *World Bank, commissioned paper*.

Chauvin, J. P., Glaeser, E., Ma, Y., and Tobio, K. (2017). What is different about urbanization in rich and poor countries? Cities in Brazil, China, India and the United States. *Journal of Urban Economics*, 98:17–49.

Corseuil, C. H. and Foguel, M. N. (2002). Uma Sugestão de Deflatores para Rendas Obtidas a Partir de Algumas Pesquisas Domiciliares do IBGE. *Mercado de Trabalho: conjuntuta e Análise - Nota Técnica*, (897):13.

Costa, D. L. and Kahn, M. E. (2000). Power Couples: Changes in the Locational Choice of the College Educated, 1940-1990. *The Quarterly Journal of Economics*, 115(November):1287–1315.

Costa, F., Garred, J., and Pessoa, J. P. (2016). Winners and losers from a commodities-for-manufactures trade boom. *Journal of International Economics*, 102:50–69.

De Barros, R. P., Carvalho, M. D., Franco, S., and Mendonça, R. (2006). Uma análise das principais causas da queda recente na desigualdade de renda brasileira. *Texo para Discussão - IPEA*, 1203.

Diamond, R. (2016). The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000. *American Economic Review*, 106(3):479–524.

Dix-carneiro, R. and Kovak, B. K. (2016). Trade Liberalization and Regional Dynamics.

Dix-Carneiro, R. and Kovak, B. K. (2017). Trade Liberalization and Regional Dynamics. *American Economic Review (forthcoming)*, pages 1–102.

Edmonds, E. V., Pavcnik, N., and Topalova, P. (2010). Trade adjustment and human capital investments: Evidence from indian tariff reform. *American Economic Journal: Applied Economics*, 2(4):42–75.

Fernandes, R. and de Felicio, F. (2005). The Entry of the Wife into the Labor Force in Response to the Husband's Unemployment: A Study of the Added Worker Effect in Brazilian Metropolitan Areas. *Economic Development and Cultural Change*, 53(4):887–911.

Foguel, M. N. (2016). The Effects of Gender Segregation at the Occupation, Industry, Establishment, and Job-Cell Levels on the Male-Female Wage Gap.

Frank, R. H. (1978). Why Women Earn Less: The Theory and Estimation of Differential Overqualification. *The American Economic Review*, 68(3):360–373.

Galor, O. and Weil, D. N. (1996). The Gender Gap, Fertility, and Growth. *The American Economic Review*, 86(3):374–387.

Gemici, A. (2011). Family Migration and LaborMarket Outcomes.

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

Glaeser, E. L. and Gottlieb, J. D. (2008). The Economics of Place-Making Policies. *Brookings Papers on Economic Activity*, 2008(1):155–253.

Glaeser, E. L. and Gottlieb, J. D. (2009). The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States. *Journal of Economic Literature*, 47(4):983–1028.

Glaeser, E. L., Gyourko, J., and Saks, R. E. (2005). Urban growth and housing supply. *Journal of Economic Geography*, 6(1):71–89.

Goldin, C. (2006). The Quiet Revolution That Transformed Women's Employment, Education, and Family. *The American Economic Review: Papers and Proceedings*, 96(2):1–21.

Goldin, C. (2014). A Pollution Theory of Discrimination. Male and Female Differences in Occupations and Earnings. In Boustan, L. P., Frydman, C., and Margo, R. A., editors, *Human Capital in History: The American Record*, number October, pages 313–348. University of Chicago Press.

Goldin, C., Kerr, S. P., Olivetti, C., and Barth, E. (2017). The Expanding Gender Earnings Gap: Evidence from the LEHD-2000 Census. *American Economic Review*, 107(May).

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

Gollin, D., Kirchberger, M., and Lagakos, D. (2017). In Search of A Spatial Equilibrium in the Developing World.

Greenwood, J., Seshadri, A., and Yorukoglu, M. (2005). Engines of Liberation. *Review of Economic Studies*, 72:109–133.

Hakobyan, S. and McLaren, J. (2016). Looking for Local Labor Market Effects of NAFTA. *Review of Economics and Statistics*, 98(4):728–741.

Hanlon, W. W. (2015). Endogenous City Disamenities: Lessons from Industrial Pollution in 19th Century Britain.

Hunt, J. (2002). The Transition in East Germany: When Is a Ten-Point Fall in the Gender Wage Gap Bad News? *Journal of Labor Economics*, 20(1):148–169.

IBGE (2002). Censo Demografico 2000: Documentacao das Microdados da Amostra.

IBGE (2016). *Arranjos Populacionais e Concentrações Urbanas do Brasil*. IBGE, Rio de Janeiro, second edition.

Johnson, M. and Keane, M. P. (2013). A Dynamic Equilibrium Model of the US Wage Structure, 1968-1996. *Journal of Labor Economics*, 31(1):1–49.

Kline, P. (2010). Place Based Policies, Heterogeneity, and Agglomeration. *The American Economic Review: Papers and Proceedings*, 100(2):383–387.

Kline, P. and Moretti, E. (2014a). Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority. *The Quarterly Journal of Economics*, 129(1):275–331.

Kline, P. and Moretti, E. (2014b). People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs. *Annual Review of Economics*, 6(1):629–662.

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

Lazear, E. P. and Rosen, S. (1990). Male-Female Wage Differentials in Job Ladders. *Journal of Labor Economics*, 8(1):106–123.

Lee, S. and Lin, J. (2017). Natural Amenities, Neighborhood Dynamics, and Persistence in the Spatial Distribution of Income. *Review of Economic Studies*, (13).

Mincer, J. (1974). *Schooling, experience, and earnings*. Columbia University Press, New York.

Moretti, E. (2004). Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data. *Journal of Econometrics*, 121(1-2):175–212.

Moretti, E. (2011). Chapter 14: Local Labor Markets. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics, vol. 4B*, volume 4, pages 1237–1313. Elsevier Inc.

Morten, M. and Oliveira, J. (2024). The Effects of Roads on Trade and Migration: Evidence from a Planned Capital City. *American Economic Journal: Applied Economics*, pages 389–421.

Neumark, D. and Simpson, H. (2015). Place-Based Policies. *Handbook of Regional and Urban Economics*, 5:1197–1287.

Notowidigdo, M. J. (2013). The Incidence of Local Labor Demand Shocks.

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

Olivetti, C. and Petrongolo, B. (2008). Unequal pay or unequal employment?: a cross-country analysis of gender gaps. *Journal of Labor Economics*, 26(4):621–654.

Olivetti, C. and Petrongolo, B. (2014). Gender gaps across countries and skills: Demand, supply and the industry structure. *Review of Economic Dynamics*, 17(4):842–859.

Paes de Barros, R., Olinto, P., Lunde, T., and Carvalho, M. (2011). The impact of access to free childcare on women's labor market outcomes: evidence from a randomized trial in low-income neighborhoods of Rio de Janeiro. *Paper prepared for the 2011 World Bank Economists' Forum.*

Partridge, M. D., Rickman, D. S., and Li, H. (2009). Who wins from local economic development? *Economic Development Quarterly*, 23(1):13–27.

Ponthieux, S. and Meurs, D. (2015). Gender inequality. In *Handbook of Income Distribution*, volume 2, pages 981–1146. Elsevier B.V., 1 edition.

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

Resende, G. M. (2013). Regional Devevelopment Policy in Brazil: A Review of Evaluation Literature. *REDES*, 18(3):202–225.

Roback, J. (1982). Wages, rents, and the quality of life. *The Journal of Political Economy*, 90(6):1257–1278.

Rosen, S. (1979). Wage-Based Indexes of Urban Quality of Life. In Mieszkowski, P. and Stras-Zheim, M., editors, *Current Issues in Urban Economics*, pages 74–104. Johns Hopkins University Press, Baltimore and London.

Scorzafave, L. G. and Menezes-Filho, N. A. (2005). Impacto da participação das mulheres na evolução da distribuição de renda do trabalho no Brasil. *Pesquisa e Planejamento Econômico*, 35(2):245–266.

Soares, S. and Izaki, R. S. (2002). A Participação Feminina no Mercado do Trabalho. *Textos para Discussão*, (923).

Sorenson, O. and Dahl, M. S. (2016). Geography, Joint Choices and the Reproduction of Gender Inequality. *American Sociological Review*, 81(5):900–920.

Topel, R. H. (1986). Local Labor Markets. *Journal of Political Economy*, 94(3):111–143.

A Model Appendix

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

A.1 Equilibrium under Autarky

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

First, I solve for the gender employment and wage gaps. Note that equations 10 and 11 together yield a supply-side gender gap expression:

$$\frac{W_{Mjt}}{W_{Wjt}} = \frac{1}{1+T_{jt}} \left(\frac{N_{Mjt}}{N_{Wjt}}\right)^{\frac{1}{\iota}} . \tag{25}$$

Combining equations 25 and 5, I obtain:

$$\frac{N_{Mj}}{N_{Wj}} = \left[(1+T_{jt}) \left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\sigma}\right]^{\frac{\iota}{1-\iota(\beta\sigma-1)}} \text{, and,} \tag{26}$$

$$\frac{W_{Mj}}{W_{Wj}} = \left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\frac{\sigma}{1-\iota(\beta\sigma-1)}} (1+T_{jt})^{\frac{\iota(\beta\sigma-1)}{1-\iota(\beta\sigma-1)}} . \tag{27}$$

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 write the aggregate effective labor used by firms in region j as:

$$L_{jt} = \left[\left(\psi_{W_{jt}} N_{Wjt}^{\beta}\right)^{\sigma} + \left(\psi_{M_{jt}} N_{Mjt}^{\beta}\right)^{\sigma}\right]^{\frac{1}{\sigma}} , \tag{28}$$

which is a component of the production function (equation 2). Using 27, I can rewrite 28 as:

$$L_{jt} = N_{Wjt}^{\beta} \left[\psi_{W_{jt}}^{\sigma} + \psi_{M_{jt}}^{\sigma} \left[(1+T_{jt}) \left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\sigma}\right]^{\frac{\beta\iota\sigma}{1-\iota(\beta\sigma-1)}}\right]^{\frac{1}{\sigma}} \text{, or,} \tag{29}$$

$$L_{jt} = N_{Mj}^{\beta} \left[\psi_{W_{jt}}^{\sigma} \left[(1+T_{jt}) \left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\sigma}\right]^{\frac{\beta\iota\sigma}{\iota(\beta\sigma-1)-1}} + \psi_{M_{jt}}^{\sigma}\right]^{\frac{1}{\sigma}} . \tag{30}$$

Labor Market for Females

Using equation 29, female labor demand can be expressed as:

$$W_{Wjt} = \lambda_1 \psi_{Wjt}^{\sigma} N_{Wjt}^{\xi_1} \Psi_{Wjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}} , \tag{31}$$

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

Equating female labor demand in 31 and labor supply in 10 yields equilibrium employment and wages:

$$N^{*aut}_{Wjt} = N_{jt}^{\frac{1}{1-\iota\xi_1}}\left(\frac{\lambda_1}{1+T_t}\right)^{\frac{\iota}{1-\iota\xi_1}}\psi_{Wjt}^{\frac{\iota\sigma}{1-\iota\xi_1}}\Psi_{Wjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}\frac{\iota}{1-\iota\xi_1}}, \tag{32}$$

$$W^{*aut}_{Wjt} = N_{jt}^{\frac{\xi_1}{1-\iota\xi_1}}\left(\frac{\lambda_1}{1+T_t}\right)^{\frac{1}{1-\iota\xi_1}}\psi_{Wjt}^{\frac{\sigma}{1-\iota\xi_1}}\Psi_{Wjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}\frac{1}{1-\iota\xi_1}}. \tag{33}$$

Labor Market for Males

Using equation 30, male labor demand can be written as:

$$W_{Mjt} = \lambda_1\psi^{\sigma}_{Mjt}N^{\xi_1}_{Mjt}\Psi_{Mjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}}, \tag{34}$$

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

Equilibrium employment and wages for men follow from equating labor demand in 34 and labor supply in 11:

$$N^{*aut}_{Mjt} = N_{jt}^{\frac{1}{1-\iota\xi_1}}\lambda_1^{\frac{\iota}{1-\iota\xi_1}}\psi_{Mjt}^{\frac{\iota\sigma}{1-\iota\xi_1}}\Psi_{Mjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}\frac{\iota}{1-\iota\xi_1}}, \tag{35}$$

$$W^{*aut}_{Mjt} = N_{jt}^{\frac{\xi_1}{1-\iota\xi_1}}\lambda_1^{\frac{1}{1-\iota\xi_1}}\psi_{Mjt}^{\frac{\sigma}{1-\iota\xi_1}}\Psi_{Mjt}^{\frac{\gamma(1-\sigma)}{(1-\gamma)}\frac{1}{1-\iota\xi_1}}. \tag{36}$$

A.1.1 Housing Rents

Equation 15 can be rewritten as:

$$R^{*aut}_{jt} = \left(\zeta\bar{W}^{*aut}_{jt}N_{jt}\right)^{\frac{1}{1+\rho}}, \tag{37}$$

with $\zeta := \frac{\alpha}{\bar{H}(\frac{1+r_t}{r_t})^{\rho}}$.

The net wage under autarky is in turn defined by the wage and employment equilibria in equations 19, 21, 20 and 22, and the average labor force participation costs of men and women in the workforce. Specifically:

$$\bar{W}^{*aut}_{jt} = \left(\frac{N^{*aut}_{Wjt}}{N_{jt}}W^{*aut}_{Wjt} - \bar{\varphi}_{Wjt}\right) + \left(\frac{N^{*aut}_{Mjt}}{N_{jt}}W^{*aut}_{Mjt} - \bar{\varphi}_{Mjt}\right). \tag{38}$$

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 given by:

$$\bar{\varphi}_{Wjt} = \frac{\iota}{\iota+1}(1+T_{ij})\left[\left(\frac{W^{aut*}_{Wjt}}{1+T_{ij}}\right)^{\iota+1} - 1\right] \text{, and,} \tag{39}$$

$$\bar{\varphi}_{Mjt} = \frac{\iota}{\iota+1}\left[(W^{aut*}_{Mjt})^{\iota+1} - 1\right] . \tag{40}$$

A.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 $\underline{U}$.

A.2.1 Spatial Indifference Curves and Local Population

Given the equilibrium rent equation in 15, the spatial indifference curve can be written as:

$$V_{jt}(\theta_j, \bar{W}^{net}_{jt}, N_{jt}) = \underline{U} = \zeta_t \theta_j (E(\bar{W}^{net}_{jt}))^{\frac{1+\rho-\alpha}{1+\rho}} N_{jt}^{-\frac{\alpha}{1+\rho}} , \tag{41}$$

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 $E(\bar{W}^{net}_{jt}) = E(\bar{W}^{net}_{Mjt}) + E(\bar{W}^{net}_{Wjt})$.

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 $(\frac{W_{Wjt}}{1+T_t})^{\iota}$ for women and W^{ι}_{Mjt} for men, as well as the average costs of the people who participate from equations 39 and 40. Combining these equations yields an expression for the expected net labor income for men and women in city j:

$$E(W^{net}_{Wj}) = \left(\frac{W_{Wjt}}{1+T_t}\right)^{\iota}\left[W_{Wjt} - \frac{\iota(1+T_t)}{\iota+1}\left(\left(\frac{W_{Wjt}}{1+T_t}\right)^{\iota+1} - 1\right)\right] \text{, and,} \tag{42}$$

$$E(W^{net}_{Mj}) = W^{\iota}_{Mjt}\left[W_{Mjt} - \frac{\iota}{\iota+1}(W^{\iota+1}_{Mjt} - 1)\right] . \tag{43}$$

A.2.2 Equilibrium Outcomes

The spatial indifference curve can also be written as an expression for the local population in terms of expected household wages (equation 16). 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 in 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 vice versa using equation 27, I can write equations 17 and 18, and ultimately the population equation in 16 in terms of male wages (rather than in terms of expected net household wages):

$$N_{jt} = \left(\frac{\zeta\theta_j}{\underline{U}}\right)^{\frac{1+\rho}{\alpha}} \times \left[W_{Mjt}^{\iota}\left(W_{Mjt}\frac{\iota(1-W_{Mjt}^{1+\iota})}{1+\iota}\right) + \left(\frac{\iota T_{Wt}(1-\Phi_{jt}^{1+\iota})}{1+\iota} + T_{Wt}^{\iota_M}W_{Mjt}\left(\frac{\psi_{Mjt}}{\psi_{Wjt}}\right)^{\sigma_M}\right)\Phi_{jt}^{\iota}\right]^{\frac{1-\alpha+\rho}{\alpha}}, \tag{44}$$

where $T_{Wt} := 1 + T_t$, $\Phi_{jt} := T_{Wt}^{\iota_M-1}W_{Mjt}(\frac{\psi_{Mjt}}{\psi_{Wjt}})^{\sigma_M}$, $\iota_M := \frac{\iota(\beta\sigma-1)}{\iota(\beta\sigma-1)-1}$, 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 22). Replacing it into equation 44 yields an 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 that in equation 15 the product of household net wages and housing rents can be written as $\bar{W}_{jt}^{*aut}N_{jt} = N_{Wjt}^{*aut}W_{Wjt}^{*aut} + N_{Mjt}^{*aut}W_{Mjt}^{*aut} - N_{jt}(\bar{\varphi}_{Wjt} + \bar{\varphi}_{Mjt})$. This in turn allows me to express population in terms of rents and the autarky solutions for employment and rents:

$$N_{jt} = \frac{N_{Wjt}^{*aut}W_{Wjt}^{*aut} + N_{Mjt}^{*aut}W_{Mjt}^{*aut} - \frac{R_{jt}^{1+\rho}}{\zeta}}{\bar{\varphi}_{Wjt} + \bar{\varphi}_{Mjt}}. \tag{45}$$

Replacing equation 45 and the autarky employment and wage solutions in equations 19 through 22 into the open-city population equation yields an expression that implicitly defines local housing 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 22 and replace N_{jt} with expression 44, 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 26 and combine it with the labor demand equation in 4 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.

B Data appendix

B.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 (monthly)	ww2.ibge.gov.br/home/estatistica/indicadores/precos/inpc_ipca/default seriesHist.shtm

B.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 an 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 a civil-service employee, or was an employer.** ***
Informally employed	PC 1980.	Individual that worked over the period of reference as an 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 their 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 (regular or supletivo de ensino medio, antigo classico, cientifico, etc. completed) based on variables V0633 and V0634.
Rent	PC 1991, PC 2010, IBGE3.	Monthly value of housing rent.*
Rent residual	PC 1991, PC 2010.	Residuals of a household-level regression of the log of rent on individual housing unit characteristics 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 (INPC) 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.

B.3 Region-Level Variables definitions

Variable	Samples	Description / comments
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 monthly 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 the share of employed adult males and the share of employed adult females.
Log of population density	PC 1980, 1991, 2000, and 2010; IPEA1.	Log of the ratio Population / Area.

Variable	Samples	Description / comments
Microregion	PC 1980, 1991, 2000, and 2010; IBGE2.	Time-consistent boundary of microregion. Definitions constructed following Kovak (2013), using IBGE's municipality family tree and aggregating MCAs to generate time-consistent microregions.
Arranjos populacionais	PC 1980, 1991, 2000, and 2010.	Time-consistent Arranjos Populacionais (AP), constructed by joining APs that share a common MCA for the 1980-2010 period.
Average log rent	PC 1991, PC 2010, IBGE3.	Monthly rent paid. The geometric average is calculated over all renter households in the region.
Average log wage	PC 1980, 1991, 2000, and 2010.	Geometric average over employed adults with positive wages.
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 either formally employed, informally employed, or unemployed.
Area (in square km)	IPEA1.	Geographic area in square kilometers, calculated by aggregating the areas of municipalities in each microregion.
Industry share in employment	PC 1980, 1991, 2000, and 2010.	Share of industry in regional employment, used to compute Bartik shocks.†

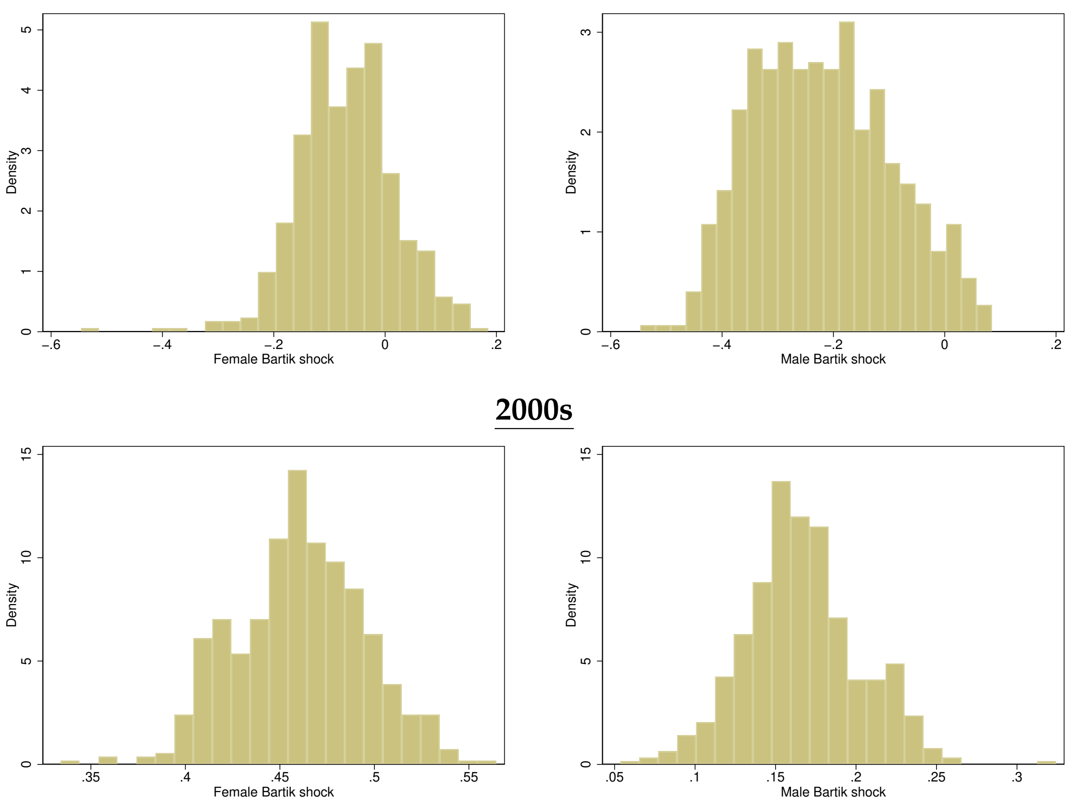
C Additional Figures and Tables

C1 Figures

Figure C1: Distributions of Gender-specific Bartik shocks

Females **Males**

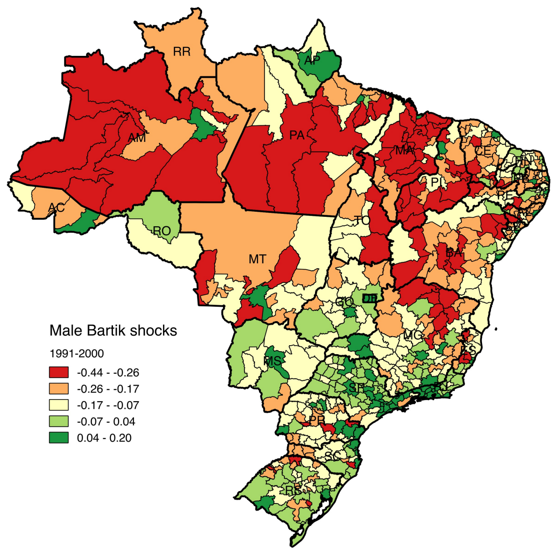
1990s



Source: Own calculations using census data.

Figure C2: Geographic distribution of gender-specific Bartik shocks, Brazil 1991-2000

Males



Females

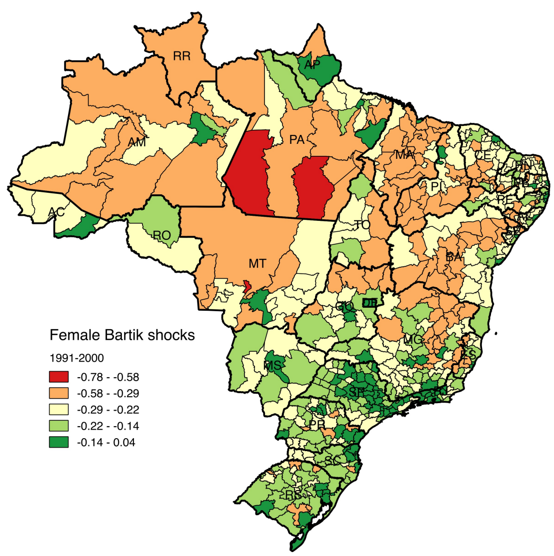
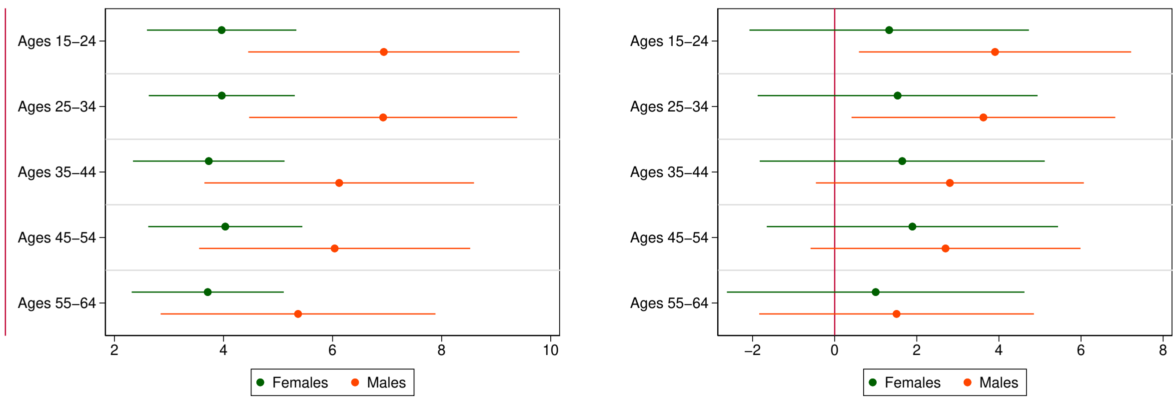


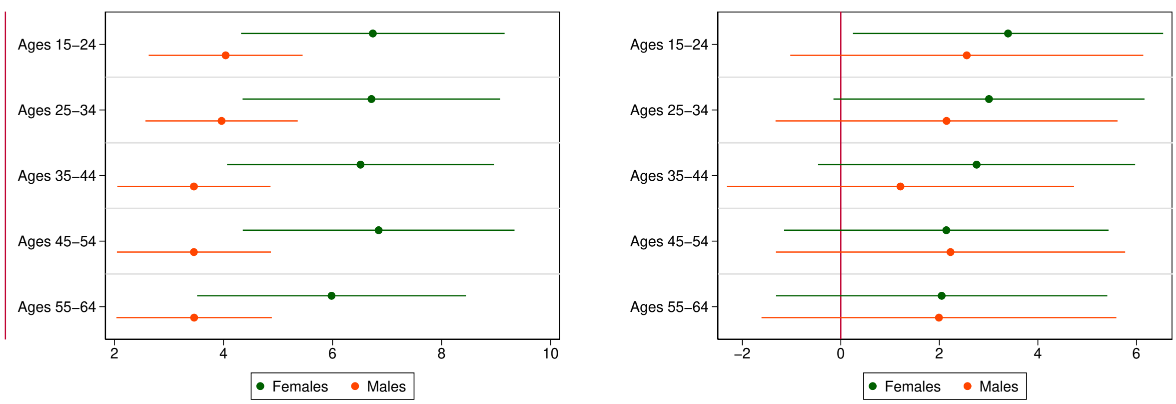
Figure C3: Effects of gender-specific shocks on migrant population by age

1990s **2000s**

Effects of own-gender shocks



Effects of other-gender shocks

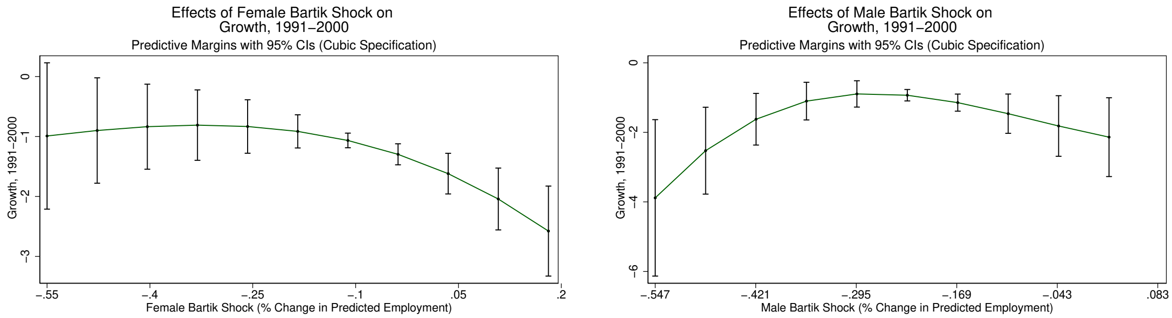


Source: Own calculations using census data.

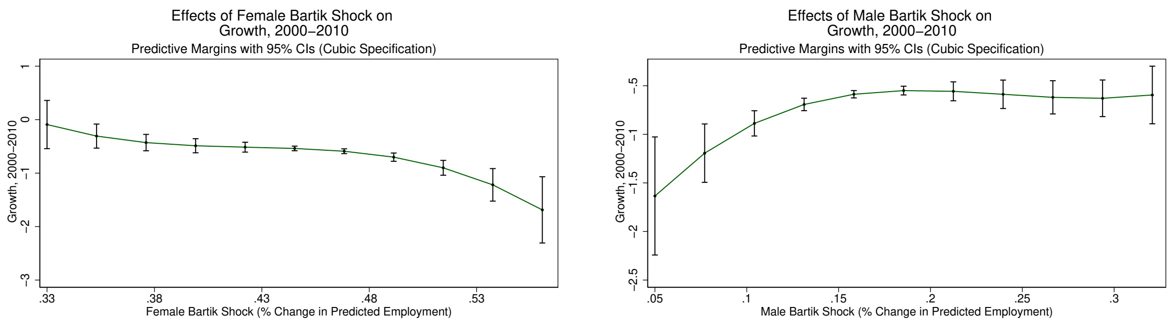
Figure C4: Effects of gender-specific shocks on the employment gap, predictive margins

Female shocks **Male shocks**

1990s



2000s

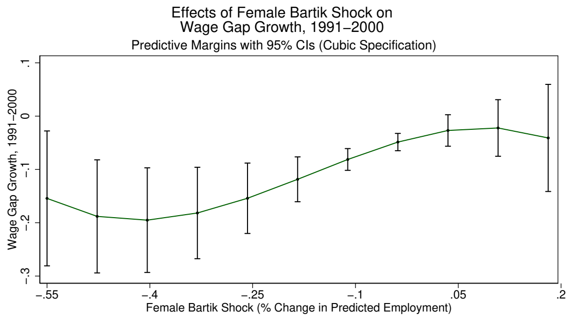


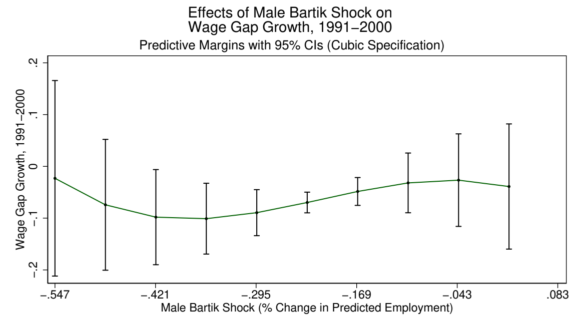
Source: Own calculations using census data.

Figure C5: Effects of gender-specific shocks on the wage gap, predictive margins

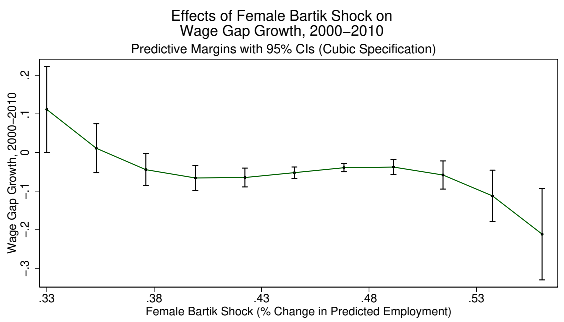
Female shocks **Male shocks**

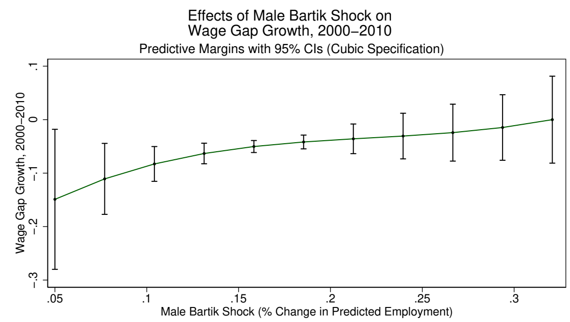
1990s





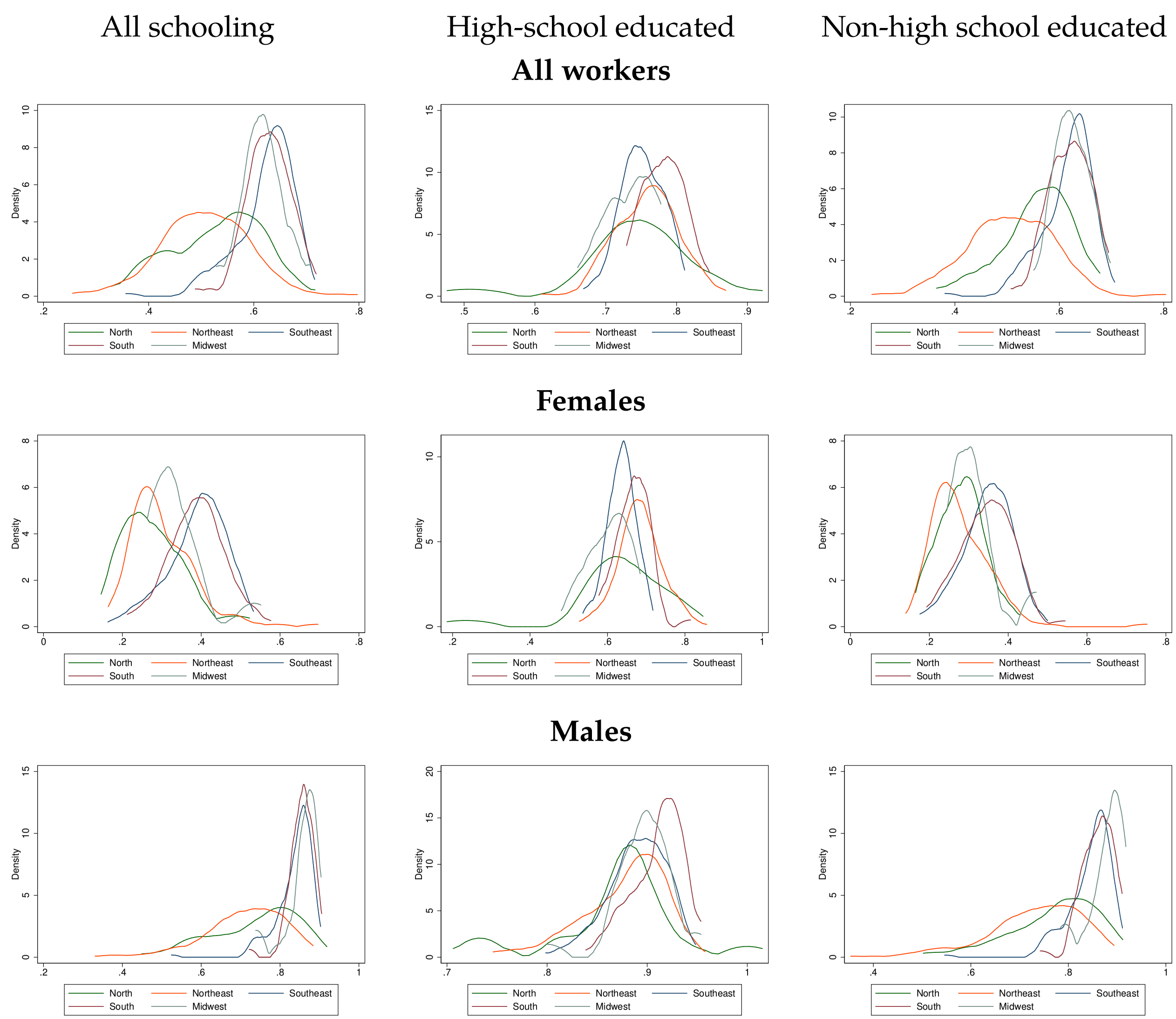
2000s





Source: Own calculations using census data.

Figure C6: Labor force participation across microregions in Brazilian macro-regions, 2000



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

C2 Tables

Table C1: 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 C2: 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 C3: 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 C4: 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 C5: 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 C6: 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 C7: 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 they moved to their current municipality of residence over the previous 10 years.

Table C8: 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

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

Table C9: 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)

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