JOBS AND GENDER: LOCAL LABOR MARKET OUTCOMES AND GENDER-SPECIFIC LABOR DEMAND

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Abstract

The labor market is characterized by a strong degree of sorting by gender into occupations and industries. Gender sorting implies that men and women are differentially exposed to changes in local labor demand. In this paper, I show that in the U.S. between 1980 and 2017, men have been more exposed to geographically concentrated changes in labor demand than women, and that men are exposed to these changes with higher variance and lower mean. I find that an aggregate labor demand analysis masks important heterogeneity by gender both in exposure and response to gender-specific labor demand. I study differential responses to these shocks by gender, including migration and labor force participation. Migratory responses are greater for men, while labor supply responses are greater for women, and these effects are larger in rural areas. I provide a decomposition of the labor demand shocks to explore mechanisms, finding that industry sectors comprising most of the identifying variation of a shock vary by both gender and region of analysis.

JEL classification: J01, J16, R11, R13, R23, R58.

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1 Introduction

Transportation and infrastructure investments have long been touted by policy makers as an opportunity to create millions of well-paying jobs while simultaneously addressing the backlog of repair and maintenance that has been growing for decades.[1] The United States has primarily focused on national employment initiatives that are geographically uniform, even when there is a high degree of local labor market heterogeneity in industrial composition. National policies tend to focus on increasing employment in infrastructure, telecommunications, and "green" jobs—jobs in industries with high shares of men relative to women.[2] Gender segregation into industries and occupations means that increases in labor demand spurred by policy may disproportionately favor men or women depending on which industries are most affected.[3]

In order to determine the overall effectiveness of job growth policy, a crucial question is: are there differences in how workers and communities adjust when there is a change in the number of jobs available for men versus women? The possibility that local job growth alters the composition of the labor force is also important to understanding these adjustments.

In this paper, I provide empirical estimates on how changes in gender-specific labor demand have differential effects on local labor market outcomes. Using commuting zone level data from the 1980-2000 Censuses and the 2010 and 2017 American Community Survey (ACS) and a standard Bartik-style instrument, I examine the relationship between gender-specific local labor de-

[1]In its most recent report card on the condition of infrastructure in the United States, the American Society of Civil Engineers estimated the cost of bringing U.S. infrastructure to a state of good repair by 2025 at $4.6 trillion (American Society of Civil Engineers, 2017).

[2]Estimates suggest that 30% of the jobs created by the American Recovery and Reinvestment Act of 2009 (ARRA) would be in just three sectors: construction, manufacturing, and mining (Romer and Bernstein, 2009). Even when policy is targeted at industries with larger shares of women, women do not necessarily reap the benefits of job growth. For instance, as part of the ARRA, a large portion of the funding was earmarked for education in the form of grants to ensure the retention of teachers. However, approximately 70% of this funding went to capital expenditures and had no effect on employment of teachers (Dupor and Mehkari, 2015). This is true in the healthcare sector as well. Chodorow-Reich et al. (2012) find that Medicare grants create job growth, but 85% of these jobs are outside the government, health, and education sectors.

[3]Blau and Kahn (2017) provide an overview of how women's relative representation across industries and occupations has affected the gender wage gap and provide a review of the literature of employment segregation by sex.

mand growth and changes in population, labor force participation, housing rents, wages, and the wage gap. I also provide a characterization of the nature of shocks to labor demand, both by geography and sector.

I find that using an aggregate labor demand instrument obscures *both* differential exposure to employment growth *and* differential responses by men and women to employment growth. This paper fits into the broad literature on the effects of aggregate labor demand changes – without a gender component – on local outcomes (Bartik, 1991; Blanchard and Katz, 1992; Bound and Holzer, 2000; Glaeser et al., 2005; Moretti, 2011; Bartik, 2015; Cadena and Kovak, 2016). This literature typically finds that migration equalizes worker utility across space, with some worker types less mobile than others. Recent work finds that although less-educated workers are not as mobile as their counterparts, they may be disproportionately compensated during adverse labor demand shocks due to declines in rental prices and increased use of social insurance programs (Glaeser et al., 2005; Notowidigdo, forthcoming). While a strain of literature focuses on male-centered shocks to employment in specific industries,[4] little is known about the extent to which gender sorting creates differential exposure to shocks or how responses to shocks of the same magnitude differ by gender. To my knowledge, this is the first paper to examine how both male and female changes in labor demand affect local area outcomes in the United States.

I find evidence that male-specific employment growth significantly increases male and female population by roughly the same amount (a 10% increase in employment increases adult population by approximately 6.5%), while female changes in employment have no significant effect on population. This points to migration responses being an important mechanism of adjustment for men, but not for women. Women may be moving with their counterparts when males experience employment growth, but the converse does not seem to be true. These findings provide support to the literature on family migration (Mincer, 1978; Jacobsen and Levin, 1997; Cooke, 2003). The growth of labor market attachment of women creates an increase in migration ties, which

[4]For example, positive shocks due to coal booms and fracking lead to increases in male migration and wages (Black et al., 2005; Kearney and Wilson, 2018). Negative shocks to manufacturing employment from import competition of Chinese goods is examined by Autor et al. (2013).

could deter migration even when faced with unemployment or poor labor market prospects.[5]

If job growth for women is not inducing migratory responses, it must be the case that there are changes in local labor supply. My findings suggest that there is both a push and pull effect for women in the labor market, depending on the gender that is experiencing job growth. I also find asymmetrical responses to job growth by gender. Women are pulled into the labor force at higher rates than men for a similar increase in predicted own-gender job growth (a 4.6% increase for women versus a 1.9% increase for men given a 10% increase in labor demand). On the other hand, job growth for males pushes women out of the labor force – decreasing female labor market participation by roughly 4.5% for a 10% increase in labor demand for men. There are several factors at work that determine a woman's response to job growth. This first is gender norms; as men enter the workforce or enjoy a strong labor market, women may have more flexibility to stay at home and raise children (Fortin, 2015; Bertrand, 2011; Bertrand et al., 2015). Second, when women are in geographical proximity to their mothers or mothers-in-law, labor force participation is 4-10 percentage points higher than those living relatively farther away (Compton and Pollak, 2014). As couples move to take advantage of jobs for men, this channel for labor force participation is reduced. The last factor is the stagnation of real wages for many low-skilled men. This may induce women into the labor market to offset the decline in their husband's earnings (e.g. Lundberg (1985), Stephens (2002), Cullen and Gruber (2000)). Meanwhile, my findings show that men are no less likely to leave the labor market when there is an increase in labor demand for women.

Gender-specific job growth also has differential effects on local area wages and the gender pay gap. For the aggregate Bartik instrument, in all specifications across gender and metro/non-metro commuting zones, an increase in jobs leads to higher wages. However, I find that when using gender-specific instruments, male employment growth increases wages for both men and women while female employment growth *decreases* both outcomes. These results are larger in magnitude for metro areas than non-metro areas. These declines are in line with previous studies such as Acemoglu et al. (2004), who find that a

[5] See Molloy et al. (2011) for a thorough discussion of trends and other possible mechanisms behind migration.

10 percent increase in relative female labor supply during WWII lowered female wages by 6 to 7 percent and also reduced male wages by 3 to 5 percent. More recent work finds that as women begin to enter occupations dominated by men, wages begin to fall in those jobs even after controlling for education, race, and work experience (Levanon et al., 2009). My findings could be a result of selection into the labor market, however there is mixed empirical evidence on whether this selection is negative (Neal, 2004; Blau and Kahn, 2006) or positive (Mulligan and Rubinstein, 2008; Olivetti and Petrongolo, 2008; Blundell et al., 2007).

For the empirical estimation, I use a strategy that creates a labor demand index that is independent of changes in local labor supply popularized by Bartik (1991). While aggregate Bartik "shift-share" instruments have been in use for some time, gender-specific labor demand instruments have only recently been explored in the literature. Lindo et al. (2018) examines the effect of such shocks on child maltreatment, Page et al. (2017) on child health, Schaller (2016) looks at fertility, and Autor et al. (2018) examines the effect of import competition shocks in manufacturing on the marriage market. The most comparable work to this research is Chauvin (2018), who examines the effects of gender-specific changes in labor demand to local markets in Brazil. My paper provides evidence that his theoretical model holds in the context of a highly developed nation. I also provide a careful decomposition of the labor demand shocks to provide more information on the drivers of the outcomes in urban versus rural areas.

There is debate on the identifying assumptions behind these instruments (for example, Adao et al. (2018); Borusyak et al. (2018); Goldsmith-Pinkham et al. (2018)). Defending the exclusion restriction becomes a bit harder with the Bartik instrument, since it is a weighted average of many different industry growth rates. I incorporate several tests to address the potential identification issues as recommended by Goldsmith-Pinkham et al. (2018): analyzing Rotemberg weights, correlation of industry composition, alternative estimators, and over-identification tests. Specifically, I decompose the gender-specific Bartik instruments into high-weight industry sectors that are potentially driving the results. This decomposition finds that these differ not only by gender, but also by metro status. In metro areas, the male-specific instrument is driven by variation in manufacturing, construction, and business services (which include computer and repair services). For women in metro areas, the instrument puts a high weight on retail trade, professional services (which includes teachers and healthcare workers), and finance, insurance and real estate. The results of this decomposition for non-metro areas differ in important ways. I find that for males in non-metro labor markets, mining replaces business services as a high-weight industry and less weight is placed on manufacturing. For women in non-metro areas, the highest-weight industry is also professional services, but the weight is double that of metro areas. Basic manufacturing replaces finance insurance and real estate as a high-weight industry for women in non-metro areas. It is important to keep this context in mind when discussing the results of a change in predicted labor demand.

My findings on the differential effects of gender-specific job growth also inform work on the debate over place-based policy. Recent arguments for the reconsideration of place-based policies center on the facts that regional convergence has stalled (Berry and Glaeser, 2005; Moretti, 2011) and labor mobility has fallen dramatically over the last few decades (Molloy et al., 2011). Rather than targeting groups of individuals for transfers, place-based policy explicitly targets particular geographic areas.[6] Place-based policy may have more impact when tailored to the underlying workforce, and this is crucial in justifying spatially heterogeneous policies (Austin et al., 2018). The effect of gender-specific labor demand growth and careful consideration of the type of underlying industrial structure of a local labor market could be an important part in determining the overall effectiveness of place-based policy.

The paper proceeds as follows. Section 2 briefly outlines and presents the main findings of the theoretical model. Section 3 outlines the empirical strategy, including construction of the instrument used for local labor demand growth. Section 4 outlines the results, Section 5 covers robustness checks, and Section 6 concludes.

2 Theoretical Model

This section outlines the theoretical model used to motivate the empirical work in Section 3. I incorporate a spatial equilibrium model adapted by Chauvin

[6]For a review of place-based policy, see Bartik (2004); Glaeser and Gottlieb (2008); Austin et al. (2018).

(2018) that builds on Rosen (1979) and Roback (1982). There is imperfect substitution between genders and each has their own productivity shifter to model the gender-specific changes in labor demand. I summarize the main points below; for complete details on these predictions and how the model closes, see Appendix C.

The theoretical model predicts several outcomes in response to gender-specific employment growth: i) gender differences stem from joint mobility constraints of married couples, ii) male job prospects carry larger weight in household location because of lower opportunity costs of labor force participation, iii) migration elasticity of households is larger with respect to male than female labor demand growth, iv) positive changes in male employment leads to larger increases in population, rents, and the gender economic gap, and v) due to tied migration, increases in labor demand to one gender increase the supply of labor of the other, with male labor demand growth having a larger effect.

2.1 Production and Labor Demand

Each commuting zone j has many homogeneous firms that are competitive and produce identical tradeable goods. The CZ-level production function is identical to the firm's, and takes the form:

$$Y_{jt} = A_{jt} L_{jt}^{\alpha} K_{jt}^{1-\alpha} \quad (1)$$

where A_{jt} is CZ-specific total factor productivity, K_{jt} is capital, L_{jt} is a CES aggregate of different labor types, and $\alpha \in (0,1)$ is the income share of labor. I allow for imperfect substitution between male and female labor by incorporating a CES gender-specific aggregate that combines male and female labor according to:

$$L_{jt} = (\theta_{Fjt} L_{Fjt}^{\rho} + \theta_{Mjt} L_{Mjt}^{\rho})^{\frac{1}{\rho}} \quad (2)$$

where $G \in \{F, M\}$ denotes a female or male, and $\sigma = \frac{1}{1-\rho}$ is the elasticity of substitution between genders where $0 \leq \rho \leq 1$. The parameters θ_{Fjt}, θ_{Mjt} represent the relative productivity levels of females and males, standardized so that $\theta_{Fjt} + \theta_{Mjt} = 1$ and any common multiplying factor can be absorbed in the A_{jt} term.

Firms operate in a perfectly competitive output market so real wages are equal to the marginal product of labor for each gender:

$$W_{Gjt} = \frac{\partial Y_{jt}}{\partial L_{Gjt}} = \alpha A_{jt} L_{jt}^{\alpha-\rho} K_{jt}^{1-\alpha} \times \theta_{Gjt} L_{Gjt}^{\rho-1} \tag{3}$$

and a frictionless capital market supplies capital perfectly elastically at price κ_t, which is constant across all commuting zones:

$$\kappa_t = \frac{\partial Y_{jt}}{\partial K_{jt}} = (1-\alpha) A_{jt} L_{jt}^{\alpha} K_{jt}^{-\alpha} \tag{4}$$

The gender wage gap for workers in CZ j depends on the gender productivity difference, how substitutable male and female labor are, and the relative number of male to female workers:

$$\frac{W_{Mjt}}{W_{Fjt}} = \left(\frac{\theta_{Mjt}}{\theta_{Fjt}}\right)\left(\frac{L_{Mjt}}{L_{Fjt}}\right)^{\rho-1} \tag{5}$$

2.1.1 Effects of changes to male and female demand on the wage gap

Changes in female and male productivity levels, θ_{Gjt}, shift the local labor demand curves. In the case of a positive shift in male labor demand, the direct effect on the wage gap will be positive ($\frac{\partial(W_{Mjt}/W_{Fjt})}{\partial\theta_{Mjt}} > 0$), but the total effect will depend also on the migratory response of males. For example, if males move into an area to take advantage of jobs, the ratio of males to females in the market will change ($\frac{\partial(L_{Mjt}/L_{Fjt})}{\partial\theta_{Mjt}} > 0$). This in turn causes a negative partial effect on the wage gap since $0 \leq \rho \leq 1$. In a similar fashion, increases in female labor demand could increase the wage gap if female migration effects dominate productivity effects.

2.2 Household Utility and Labor Supply

Households choose locations to maximize a joint Cobb-Douglas utility function that consists of consumption, housing, and amenities. I use a framework of joint mobility constraints as outlined in Chauvin (2018). Each household consists of two members, a female (F) and a male (M). Each individual is endowed with one unit of labor, and faces a labor force participation cost φ_i drawn from distribution $F(\varphi_i)$. The labor force participation cost is an exogenous and stochastic draw from a power law with CDF $F(\varphi_i) = (\frac{\varphi_i}{\varphi_{min}})^{\gamma}$, where $\gamma \in [0,1]$ and has support $\varphi_i \in (1, \varphi_{max})$ for males and $\varphi_i \in (1+T_t, \varphi_{max})$ for women. The assumption of this model is that females always face a higher starting support value than males by T_t.[7]

After observing local wages, rents, and amenities of an area, households choose a location. They know the distribution of labor market participation costs $F(\varphi_i)$ in advance, but only realize their exact costs, φ_i, after the choice has been made. They then choose whether or not to participate in the labor market or to stay at home in domestic production.

Each household i derives utility from location amenities, Λ_j, consumption of a nationally traded good, C_{ijt}, normalized to the price of one, and housing, H_{ijt}, at a cost of R_{jt}. Workers' relative taste for consumption goods versus housing is governed by β, where $0 \leq \beta \leq 1$. Households maximize utility according to:

$$max\{\Lambda_j C_{ijt}^{1-\beta} H_{ijt}^{\beta}\} \text{ s.t. } W_{ijt}^{net} = C_{ijt} + R_{jt}H_{ijt} \tag{6}$$

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

$$W_{Gjt}^{net} = \begin{cases} W_{Gjt} - \varphi_{Gt} & \text{if the person works} \\ 0 & \text{if the person does not} \end{cases}$$

Individuals sort into the labor market if their wage is greater than their participation cost ($\varphi_{gt} < W_{Gjt}$), and are indifferent to participation in the labor market if ($\varphi_{gt} = W_{Gjt}$). Female labor supply is then given by $L_{Fjt} = L_{jt}\left(\frac{W_{Fjt}}{1+T_t}\right)^{\gamma}$ and male labor supply is $L_{Mjt} = L_{jt}W_{Mjt}^{\gamma}$, therefore the implied inverse labor supply functions for females and males, respectively, are

$$W_{Fjt} = (1+T_t)\left(\frac{L_{Fjt}}{L_{jt}}\right)^{\frac{1}{\gamma}} \tag{7}$$

[7] Overall costs of labor force participation for both genders include things like childcare, commuting, and job search costs. The additional labor force participation costs born by women are reflected in substantial empirical work, including Ponthieux and Meurs (2015); Killingsworth and Heckman (1986) amongst others.

$$W_{Mjt} = \left(\frac{L_{Mjt}}{L_{jt}}\right)^{\frac{1}{\gamma}} \tag{8}$$

From Equation 6, the optimal level of housing consumption is derived as:

$$H^*_{ijt} = \beta \frac{W^{net}_{ijt}}{R_{jt}} \tag{9}$$

and the indirect utility function for household i is then:

$$V_{ijt}(\Lambda_j, W^{net}_{ijt}, R_{jt}) = \beta^\beta (1-\beta)^{1-\beta} \Lambda_j W^{net}_{ijt} R^{-\beta}_{jt} \tag{10}$$

In spatial equilibrium, indirect utility is equalized across space for the marginal household. Households move to areas where rents are cheaper or wages are higher. The increase in population causes an increase in demand for housing and rents increase in turn. Eventually, all households are sorted so that wages, rents, and amenities are equalized across space and all households face the same utility level $V_{ijt}(\Lambda_j, W^{net}_{ijt}, R_{jt}) = \underline{U}$.[8]

2.3 Housing Market

Local prices are set through equilibrium in the housing market. Local housing demand is an aggregate of the individual housing demand function (given in Equation 9):

$$\begin{aligned} H^D_{jt} &= \beta \frac{\bar{W}^{net}_{jt}}{R_{jt}} \times L_{jt} \\ \bar{W}^{net}_{jt} &= \left(\frac{L_{Mjt}}{L_{jt}} W_{Mjt} - \bar{\varphi}_{Mjt}\right) + \left(\frac{L_{Fjt}}{L_{jt}} W_{Fjt} - \bar{\varphi}_{Fjt}\right) \end{aligned} \tag{11}$$

where $\bar{W}^{net}_{jt}$ are the average net wages for households in the local area and $\bar{\varphi}_{Gjt}$ is the average participation cost for each gender that sorts into the workforce.

Housing supply is a function of national interest rates (r_t) and construction costs (CC_{jt}). Housing belongs to absentee landlords, who buy it from developers and rent it to local residents for R_{jt}. With free entry and zero-profit

[8]The model assumes no moving costs.

conditions, developers earn a profit given by:

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

Developers sell housing at the cost of construction, $\frac{(1+r_t)}{r_t}R_t = CC_{jt}$. Additional units can be provided at higher construction costs with an elasticity of ζ: for a given construction cost, there is a supply of $\bar{H} \times CC_{jt}^{\zeta}$ units of housing. The local housing supply is then given by:

$$H^S_{jt} = \bar{H}\left(\frac{(1+r_t)}{r_t}\right)^{\zeta} R^{\zeta}_{jt} \tag{12}$$

Equating housing demand and supply, equilibrium rents become:

$$R^*_{jt} = \left(\beta \frac{\bar{W}^{net}_{jt}}{\bar{H}\left(\frac{1+r_t}{r_t}\right)^{\zeta}} L_{jt}\right)^{\frac{1}{1+\zeta}} \tag{13}$$

2.4 Summary of the model

Using the spatial equilibrium assumption that utility is equalized across space, I can re-write the indirect utility function to express local population in terms of expected net household wage. This wage enters the utility function as an expectation due to the fact that there is uncertainty about each gender's labor force participation costs.

$$L_{jt} = \left(\frac{\xi\Lambda_j}{\underline{U}}\right)^{\frac{1+\zeta}{\beta}} \left(E[W^{net}_{jt}]\right)^{\frac{\zeta+1-\beta}{\beta}} \tag{14}$$

where $\xi = \beta^{\beta}(1-\beta)^{1-\beta}\big(\beta/\bar{H}(\frac{1+r_t}{r_t})^{\zeta}\big)$ and $E[W^{net}_{jt}] = E[W^{net}_{Fjt}] + E[W^{net}_{Mjt}]$.

The gender-specific expected net labor income for females and males in each commuting zone (following from the functional form assumption on $F(\varphi_i)$):

$$E(W^{net}_{Fj}) = \underbrace{\left(\frac{W_{Fjt}}{1+T_t}\right)^{\gamma}}_{\text{P(participating)}} \left[W_{Fjt} - \underbrace{\left(\frac{\gamma(1+T_t)}{\gamma+1}\left(\left(\frac{W_{Fjt}}{1+T_t}\right)^{\gamma+1} - 1\right)\right)}_{\bar{\varphi}_{Fjt}}\right] \tag{15}$$

$$E(W_{Mj}^{net}) = \underbrace{\left(W_{Mjt}\right)^{\gamma}}_{\text{P(participating)}} \left[W_{Mjt} - \underbrace{\left(\frac{\gamma}{\gamma+1}\left(W_{Mjt}^{\gamma+1} - 1\right)\right)}_{\bar{\varphi}_{Mjt}}\right] \tag{16}$$

The model's key implications depend on how migrants react to changes in expected gender-specific wages. In expectation, female wages are penalized by a cost (T_t). Changes in labor demand that affect the wages of males should have a larger migratory response — as evidenced by changes in population — than equivalent changes to female labor demand. Larger populations increase housing demand and thus increase equilibrium rents. This effect, according to the model, should also be larger for men than for women if migratory responses are greater for men.

3 Empirical Estimation

In this section, I show how population, labor force participation, housing rents, wages, and the wage gap respond to gender-specific labor employment growth. I use commuting zones as the level of analysis. Commuting zones (CZs) are clusters of counties that have the commuting structure of a local labor market, first introduced by Tolbert and Sizer (1996). Using CZs has advantages over using individual counties, metropolitan areas, or states as a definition of local labor markets since they span the entire United States; this allows for the measurement of effects for the entire country rather than just metropolitan areas. CZs are also grouped together based on commuting flows – and not arbitrarily constrained by state lines – implying economic integration.[9] Figure 1 shows the 1990 population for the 722 time-consistent commuting zones.

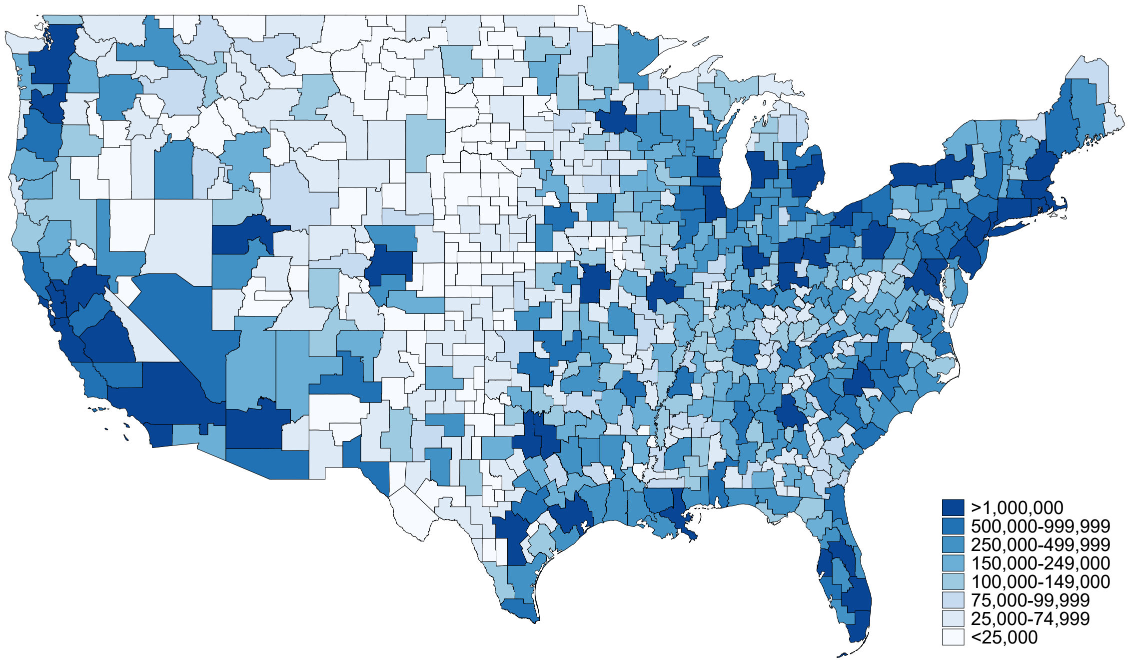
3.1 Data

The panel of commuting zones comes from the 1980, 1990, and 2000 Census 5% sample and the 2010 and 2017 American Community Survey (ACS) individual- and household-level extracts from the Integrated Public-Use Microsamples (IPUMS) database (Ruggles et al., 2018). The sample of adults

[9] These CZs are constructed as outlined in Autor et al. (2013). For more details, see Appendix B. Commuting zones in Alaska and Hawaii are omitted from the analysis.

used in this analysis consists of all individuals aged 16-64 that are not incarcerated or institutionalized and who lived in one of the 722 time-consistent commuting zones (CZs). The IPUMS data is used to construct estimates of local area wages, employment, population, housing prices, and rental prices, by gender if applicable. The data is also used to construct the labor demand instrumental variables as described in Section 3.2.

Figure 1: Boundaries and Population of US Commuting Zones (1990)



Population, employment, and housing values can also be influenced by local amenities of a particular area. To account for this, I use a natural amenity scale constructed by the U.S. Department of Agriculture (USDA) based on six measures of climate, topography, and water area that reflect environmental qualities most people prefer: warm winter, winter sun, temperate summer, low summer humidity, topographic variation, and water area (McGranahan, 1999). This scale is given at the county level; since most CZs span several counties, I use the average of all counties in a given commuting zone. When categorizing CZs into metro and non-metro areas, I use the Rural-Urban Continuum Codes provided by the USDA Economics Research Service. These codes categorize each county as metro or non-metro. For commuting zones that span several counties, I categorize them based on their highest classification.

Table A.9 in Appendix A reports descriptive statistics for all outcome and control variables used in the analysis.

The effect of changes in labor demand on the outcome variables are found by fitting the reduced form estimating equation given by:

$$\Delta y_{jt} = \beta \Delta \text{Labor Demand}_{jt} + \boldsymbol{X'_{jt}}\delta + \epsilon_{jt} \tag{17}$$

where y is the outcome of interest and Δ represents the percentage change over the respective time period in CZ j. This outcome may or may not be gender-specific. For instance, local rents and housing values do not have a gender component. The coefficient of interest is β; how the CZ-level change in labor demand affects the outcome. When analyzing the gender-specific effects, I use two additive subcomponents: female and male changes in labor demand.

Following (Autor et al., 2018), the control vector, $\boldsymbol{X_{jt}}$, contains a set of start-of-period controls at the commuting zone level: share of population that is female, share that is black, Hispanic, Asian, and other, share in age categories, share that has veteran status, share that is foreign born, share of college graduates and share with less than a high-school diploma, average number of children per household, a dummy if the CZ contains a metro area, and an amenity score.[10] Each regression also includes year and region fixed effects for each of the nine Census regions, has robust standard errors clustered at the state level, and are weighted by the product of adult population in each CZ multiplied by 1/10 times period length.

Using changes in total employment at the commuting zone level directly in Equation 17 as a measure of labor demand is problematic. It is likely to be endogenous to the outcome of interest as it captures both changes in labor supply and labor demand. The next section outlines the instrumental variables strategy I use to address this issue.

[10] A discussion of the construction of the amenity score is discussed in the Data Section and Appendix B.

3.2 Instrument for Gender-Specific Labor Demand Growth

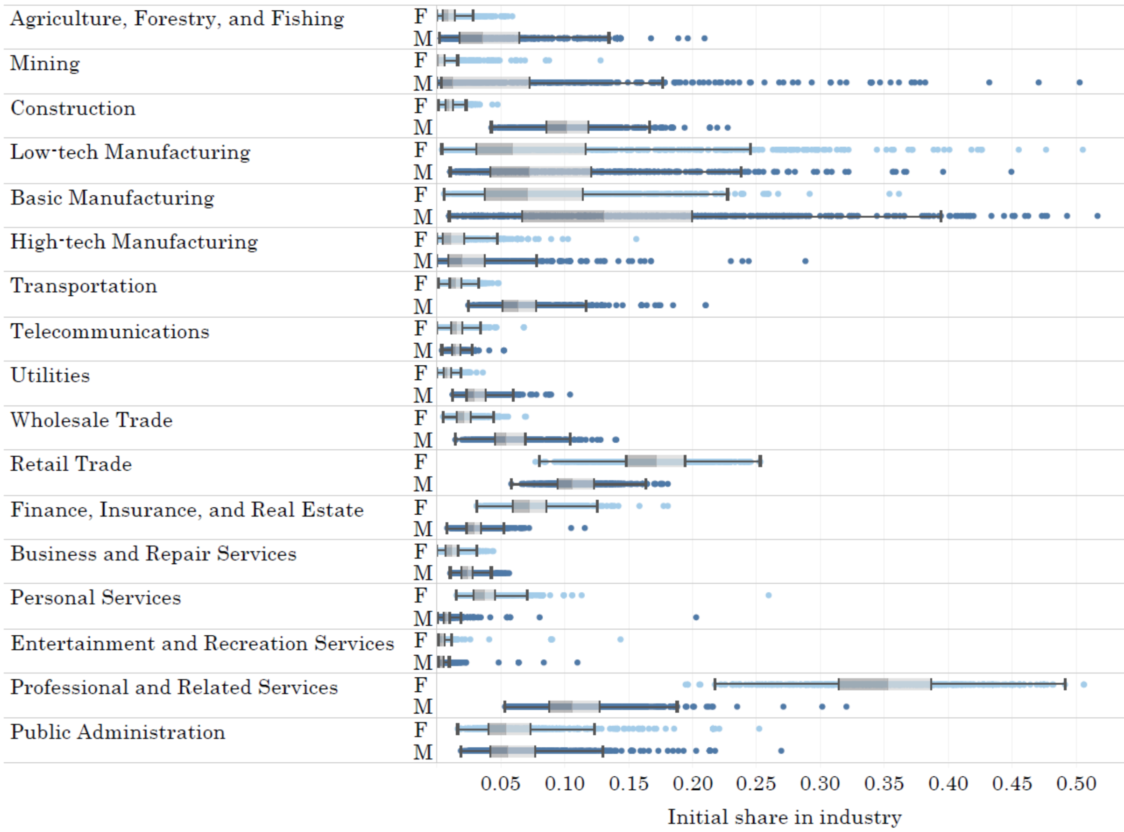
In order to estimate the reduced form equation in Equation 17, I need a measure that captures *demand*-driven changes in employment. I use a common empirical strategy stemming from Bartik (1991).[11] This creates an instrumental variable that interacts a CZ's initial share of total employment in each industry with the nation-wide industry employment growth. The higher the initial share, the more exposed a CZ is to an exogenous national shock to productivity in an industry.

Initial employment shares are fixed so that changes in employment do not reflect selective sorting across industries over this period. Initial shares by gender for each industry sector and their distribution across commuting zones can be found in Figure 2. I use 17 industry categories following Katz and Murphy (1992): (1) agriculture, forestry and fishing; (2) mining; (3) construction; (4) low-tech manufacturing (lumber, furniture, stone, clay, glass, food, textiles, apparel and leather); (5) basic manufacturing (primary metals, fabricated metals, machinery, electrical equipment, automobile, other transport equipment (excluding aircraft), tobacco, paper, printing, rubber, and miscellaneous manufacturing); (6) high-tech manufacturing (aircraft, instruments, chemicals, petroleum); (7) transportation; (8) telecommunications; (9) utilities; (10) wholesale trade; (11) retail trade; (12) finance, insurance, and real estate; (13) business and repair services; (14) personal services; (15) entertainment and recreation services; (16) professional and related services; and (17) public administration.

Shares are relatively higher for women in Professional and Related Services (which includes teachers and healthcare workers), Finance, Insurance, and Real Estate, and Retail Trade. Men have relatively larger shares in Mining, Construction, and Basic Manufacturing. However, the variation of concentration in these male-dominated sectors is much larger across commuting zones.

[11] Other work includes Katz and Murphy (1992), Blanchard and Katz (1999), and Notowidigdo (forthcoming), among others.

Figure 2: Initial share in industry by gender (1980)



Each dot represents one of the 722 commuting zones. F=female, M=male.

The instrument used for labor demand growth is computed as follows:

$$\text{Bartik}_{jt} = \sum_{k=1}^{17} \underbrace{\frac{L_{jkt_o}}{L_{jt_o}}}_{\substack{\text{CZ initial}\\ \text{employment share}\\ \text{in industry } k}} \times \underbrace{\frac{e_{-jkt} - e_{-jk,t-t_o}}{e_{-jk,t-t_o}}}_{\substack{\text{National growth of}\\ \text{industry k employment}}} \tag{18}$$

The fraction L_{jkt_o}/L_{jt_o} is the share of industry k in CZ j's total employment in 1980 and e_{-ikt} is the national employment share of industry k excluding CZ j. This "leave-one-out" technique for national employment growth addresses concerns that own-region employment may mechanically increase the predictive power of the instrument (Autor et al., 2013).[12]. The instrument predicts what the growth in a region's employment would have been if the local indus-

[12]Annual growth rates by year and industry are shown in Figure A.1

try shares had remained the same as in the starting year ($t_o = 1980$) and local employment had grown at the national industry-level rate.

I construct gender-specific measures in a similar fashion. To do so, I exploit the fact that male and female initial shares of employment differ across industries. I construct two versions of the Bartik instrument that incorporate this gender component:

$$\text{Bartik}_{jt}^{g} = \sum_{k=1}^{17} \frac{L_{jgkt_o}}{L_{jgt_o}} \times \frac{e_{-jkt} - e_{-jk,t-t_o}}{e_{-jk,t-t_o}} \tag{19}$$

Here, $g \in \{m, f\}$ indexes gender groups (male or female).

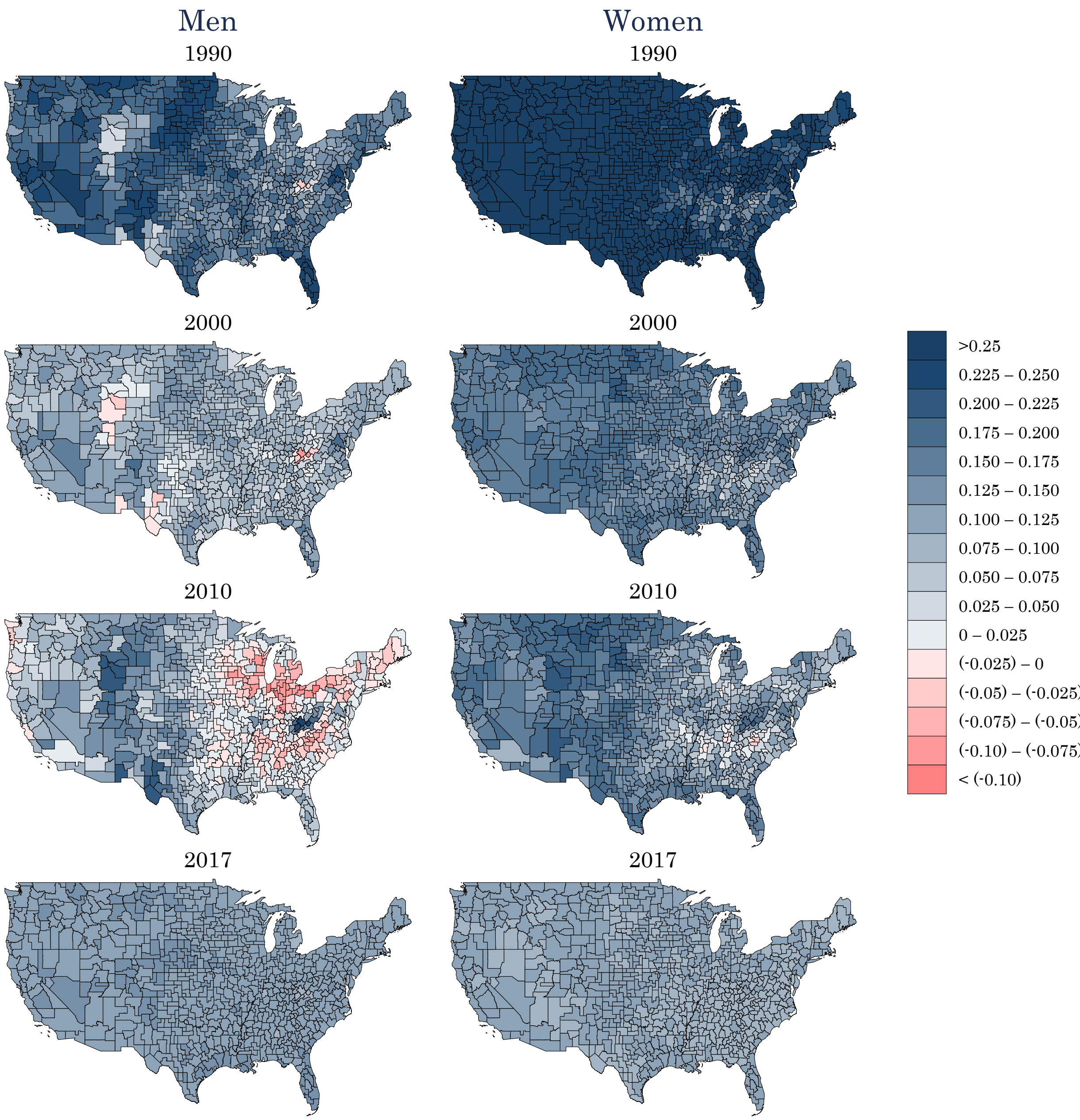
Predicted labor demand growth is largest for both genders in the ten years between 1980-1990, and slows over the following three time periods. This is most pronounced for men, where predicted employment growth slows from 17.8% over 1980-90 to just 0.016% over 2000-10. The values for the female Bartik instrument is larger in magnitude than the male Bartik for almost all time periods, owing mostly to the strong exposure to service industries and the growth of employment in these sectors. Metro CZs had larger predicted employment growth in all but the period that encompassed the Great Recession (2000-10) than non-metro CZs. Table A.1 provides summary statistics for all commuting zones as well as a break-down by metro status.

Figure 3 maps the gender-specific Bartik instruments for men and women over each time period. Variation in predicted employment growth for men is more geographically concentrated than for women. This is particularly true of the upper Midwest, where losses in the manufacturing sector were substantial. This is also true of areas that have large employment shares in mining, such as West Virginia and parts of the Dakotas. Predicted employment growth for women tends to be evenly distributed across the United States.

3.3 Identifying assumptions and potential issues

For all tables reported in the results section, tests of both under-identification and weak identification are reported for each endogenous regressor separately,

Figure 3: Gender-specific Bartik Instruments – Predicted Labor Demand Growth by Commuting Zone



using the method of Sanderson and Windmeijer (2016).[13] In the results that follow, these statistics reject weak identification.

[13]This is a modification and improvement of Angrist and Pischke (2008). The SW estimator gives a corrected version of the first-stage F statistic that is suitable for the regression two endogenous variables (male and female Bartik instruments)

Some additional conditions must also be satisfied: national employment growth rates by industry must not be correlated with CZ-level labor supply shocks, no industry can be concentrated in a particular commuting zone, and there must be sufficient cross-sectional variation in initial-period industry composition. Following Schaller (2016) and Blanchard and Katz (1999), I use 17 broad industry categories and ensure these conditions are verified in the data.[14]

Additionally, identification when using Bartik-style instruments is driven by local industry shares (Goldsmith-Pinkham et al., 2018). The key identifying assumption for the instruments is that initial local industry shares are not correlated with the time-period changes in the error term, conditional on controls. I implement several tests suggested in Goldsmith-Pinkham et al. (2018) to address these potential identification issues: (1) Rotemberg weights, (2) correlation of industry composition, and (3) alternative estimators and over-identification tests. These tests and their results are outlined below.

3.3.1 Rotemberg weights and correlates of industry composition

The Bartik instrument interacts national industry-level employment growth with each CZ's initial share of employment in the industry. However, the Bartik instrument itself does not reveal anything about the relative importance of each industry share in determining parameter estimates in the analysis. Rotemberg weights decompose the Bartik estimator into a weighted combination of just-identified estimates based on each instrument. In doing so, high-weight instruments can be identified. In this paper, each instrument corresponds one of the 17 industry sectors. Industry sectors with high Rotemberg weights are more sensitive to misspecification, and are therefore the most important to justify.

[14] See Section 3.2 for a breakdown. I also examine how different industry sector definitions alter the results. First, I construct a 20-industry sector version of the above with professional and related services disaggregated to health services, education services, child care services, and other professional services. I do this to disaggregate the sector that had the highest average initial shares of females. I then use each 1990 Census Bureau 3-digit industrial classification with (236 categories total). Constructing the Bartik instrument using either of these definitions yields similar results.

I decompose both the aggregate and the gender-specific Bartik instruments into high-weight industry sectors that are potentially driving the results.[15] Industry sectors with higher weights account for a higher share of the identifying variation. I find that specifications using the aggregate Bartik generate weights on industries that differ from the gender-specific instruments, and these weights also vary when the sample is disaggregated by metro status.

I first analyze the specification that includes all commuting zones and uses the aggregate Bartik instrument. I compute the Rotemberg weights of the Bartik estimator with controls, aggregated across time periods. The distribution of sensitivity is skewed, so that a few industry sectors have a large share of the weight. Table A.7 shows that the top three sectors are Basic Manufacturing; Finance, Insurance, and Real Estate; and Business and Repair Services. They account for roughly fifty percent (0.757/1.33) of the positive weight in the estimator.[16] When I separate the sample by metro status, I find that metro areas have identical high-weight industries with roughly the same magnitude of the weights. For non-metro areas however, the top three sectors change to Basic Manufacturing, Mining, and Professional and Related Services. These results reflect that the variation in the data the estimator is using is different for metro and non-metro areas.

I next examine weights on the gender-specific Bartik instruments, first for all commuting zones, and then by metro status. I find important differences. For men, Construction and Basic Manufacturing carry high weights across specifications. However, Mining replaces Business and Repair Services for men in non-metro areas. For women in metro areas, the female-specific instrument is driven by changes in Finance, Insurance, and Real Estate; Professional and Related Services; and Retail Trade. For women in non-metro labor markets, Professional and Related services is also highly weighted, but the weight is double that of metro areas. Basic manufacturing replaces Finance, Insurance, and Real Estate as a high-weight industry for women in non-metro areas.

[15] For details on the decomposition, see Goldsmith-Pinkham et al. (2018). Since this procedure is designed for one endogenous variable, the cross-gender Bartik was used as a control when calculating the gender-specific weights.

[16] I provide a full summary of Rotemberg weights for one regression using the aggregate Bartik instrument in Tables A.5 and A.6.

Once these high-weight industries are identified, the relationship between industry composition and local characteristics that may be correlated with labor supply shocks can be explored further. To minimize omitted variable bias, it is important to determine if the initial industry shares – which are fixed – are correlated with initial period characteristics. This is especially true of industries with the highest Rotemberg weights. To come up with a specification that controls for many observable confounders, I regress the high-weight initial industry shares and the gender-group Bartik instruments with a number of initial period characteristics of commuting zones.

To address the concerns raised by the correlation with initial-period characteristics, I include a set of start-of-period controls at the commuting zone level: share of population that is female, share that is black, Hispanic, Asian, and other, share that has veteran status, share that is foreign born, share of college graduates and share with less than a high-school diploma. I also include an amenity score, average number of children per household, and a dummy variable for whether or not the CZ includes a metro area. My preferred specification also includes year and region fixed effects for each of the nine census regions (following Autor et al. (2013).)

Like other papers in this literature, I cannot rule out the presence of potential unobservables. If the gender-specific instruments are correlated with other start-year variables even after the addition of my controls, the identification strategy would be invalid. In order to check for these issues, I look at several variables not included in my controls and compare correlations to the gender-specific instruments before and after controls are introduced. I give an example of this in Appendix A, Figure A.2, which compares a simple regression of the male-specific instrument to initial share of the adult population with only a high school degree. These results are reassuring in that the controls included in my regression specification are effective at controlling for other potential unobservables.

3.3.2 Alternative Estimators and Over-identification

According to (Goldsmith-Pinkham et al., 2018), it is useful to compare Bartik estimates over different specifications for clues to misspecification. I compare OLS, 2SLS, 2SLS with a disaggregated Bartik instrument, and the two-step efficient generalized method of moments (GMM) estimators. I compare all specifications with and without controls and observe how much the point estimates change between them. I also make use of the disaggregated Bartik (using each individual industry sector as its own instrument) to test for over-identification as a second check against misspecification. These tests are discussed in full detail in Section 5 and reveal that using the gender-specific instruments perform better than the aggregate instrument alone.

4 Results

This section presents the results from the 2SLS reduced form regressions described in Section 3. These results reflect time-period changes (1980-90, 1990-2000, 2000-10, and 2010-17) at the commuting zone level, with Bartik instruments for changes in labor demand. Again, the reduced form estimating equation is given by:

$$\Delta y_{jt} = \beta \Delta \text{Labor Demand}^{g}_{jt} + \boldsymbol{X'_{jt}}\delta + \epsilon_{jt}$$

The first stage being:

$$\Delta \text{Labor Demand}^{g}_{jt} = \gamma \text{Bartik}^{g}_{jt} + \boldsymbol{X'_{j,t}}\psi + \mu_{jt}$$

where y is the outcome of interest and Δ represents the percentage change over the respective time period in CZ j. The change in labor demand (ΔLD) is instrumented using the Bartik instrument described in Equation 18. When performing gender-specific estimates, the instrument $Bartik_{jt}$ is replaced with both $Bartik^{m}_{jt}$ and $Bartik^{f}_{jt}$ in the analysis to represent change in male labor demand ($\Delta MaleLD$) and female labor demand ($\Delta FemaleLD$), respectively. Although I am interested in the gender-specific shocks, I provide the details of the total shock ($Bartik_{jt}$) for comparison to previous research.

4.1 Population and Labor Force Participation

Table 4.1 presents the results for the regressions of the percent change in adult population and labor force participation as dependent variables. The aggregate Bartik instrument without introducing gender is presented in Panel

A, Section I. Here, increases in total employment growth have a positive effect on population growth. A 10% increase in employment is correlated with a 5.15% increase in total population, a 5.24% increase in male population, and a 5.08% increase in female population.

Table 4.1: Adult Population and Labor Force Participation – All Commuting Zones. Dependent Variables: Percentage change in all, male, and female adult population and labor force participation

	A. Percent change - population			*B. Percent change - LFP*		
	I. Aggregate Labor Demand Growth					
	All	Male	Female	All	Male	Female
Δ Total LD	0.515***	0.524***	0.508***	0.084**	0.101**	0.036
	(0.12)	(0.12)	(0.12)	(0.04)	(0.03)	(0.05)
	II. Male – Female Labor Demand Growth					
	All	Male	Female	All	Male	Female
Δ Male LD	0.684***	0.751***	0.619***	-0.073	0.154***	-0.490***
	(0.11)	(0.10)	(0.11)	(0.04)	(0.03)	(0.06)
Δ Female LD	-0.132	-0.183	-0.082	0.149**	-0.042	0.489***
	(0.20)	(0.20)	(0.21)	(0.07)	(0.06)	(0.09)
Mean Dep Var	0.106	0.111	0.101	0.016	-0.014	0.054
Level in 1990	1,830,589	896,838	833,750	.78	.87	.69
First Stage Statistics				*Total*	*Male – Female*	
Sanderson-Windmeijer F-Statistic				45.48	116.83	73.95
Prob>F				0.000	0.000	0.000

Notes: N=2,888 (722 CZ x 4 time periods). All models include initial-period controls for share of CZ population that is female, black, Hispanic, Asian, or other, veteran status, foreign born, share in age categories, share of college graduates, average number of children per household, amenity score, and a dummy if the CZ has a metro area. All models include year and Census region fixed effects, and are weighted by start-of-period CZ share of total population × 1/10 × period length. Standard errors in parentheses, * $p < .10$, ** $p < .05$, *** $p < .01$

Asymmetries appear when the Bartik instrument is separated into its gender-specific components. Panel A, Section II separates the effects of increases in labor demand on adult population. Male employment significantly increases total, male, and female populations by roughly the same amount (a 10% increase in employment increases population by approximately 7%), while female changes in employment have no significant effect on any of the population categories. This points to migration responses being an important mechanism of adjustment for men, but not for women. This also suggests that women may be moving with their counterparts when males experience employment growth, but the converse may not be true. This is also related to the types of job growth men are faced with: industries like mining and manufacturing are very place-specific and tend to be geographically concentrated. Women have larger shares in service industries, where jobs are more geographically distributed.

If female-specific labor employment growth is eliciting smaller migration responses in women, then it must be the case that there are changes in the local labor supply. In the theoretical model, own-gender employment growth is expected to be a positive factor in increasing labor force participation for both men and women, but larger for men (due to increased labor force participation costs for females). I access whether this is the case in Panel B of Table 4.1.

The aggregate Bartik instrument is presented in Panel B, Section I. In this specification, increases in labor demand have small effects on total labor force participation. For a 10% increase in employment, male LFP increases by 1% while female LFP remains unchanged. However, the aggregate Bartik analysis obscures underlying effects of gender-specific employment growth. My findings suggest that there is both a push and pull effect for women in the labor market, depending on which gender is experiencing job growth. Women are pulled into the labor force at larger rates than men for a similar increase in own-gender job growth, as shown in Table 4.1, Panel B, Section II. Women increase their LFP rates by 4.89% compared to a 1.54% increase for men given a 10% increase in labor demand. On the other hand, job growth for males pushes women out of the labor force by roughly 4.9%. This may be due to gender norms; as men enter the workforce or enjoy a strong labor market, women may have more flexibility to stay at home and raise children. However, the converse does not seem to be true. Men are no less likely to leave the labor market when there is an increase in labor demand for women.

Do these asymmetrical responses in labor force participation vary across geography? I look at this issue with results presented in Table 4.2 that disaggregates the sample by metro status. I find that “push and pull” effects are relatively larger in non-metro areas. Labor force participation rates increase

Table 4.2: Labor Force Participation Changes – Metro vs Non-Metro Commuting Zones. Dependent variables: Percentage change in total, male, and female labor force participation

	A. Non-Metro LFP			*B. Metro LFP*		
	I. Aggregate Labor Demand Growth					
	All	Male	Female	All	Male	Female
Δ Total LD	0.199***	0.212***	0.120	0.096**	0.103**	0.063
	(0.04)	(0.04)	(0.07)	(0.05)	(0.04)	(0.07)
	II. Male – Female Labor Demand Growth					
	All	Male	Female	All	Male	Female
Δ Male LD	-0.105*	0.114**	-0.564***	0.012	0.257***	-0.370***
	(0.06)	(0.05)	(0.09)	(0.07)	(0.06)	(0.09)
Δ Female LD	0.319***	0.103	0.722***	0.086	-0.132	0.405***
	(0.08)	(0.06)	(0.15)	(0.10)	(0.09)	(0.13)
Mean Dep Var	0.018	-0.021	0.072	0.016	-0.013	0.052
Level in 1990	.75	.86	.65	.79	.88	.70
First Stage	*Bartik*	*Male – Female Bartik*		*Bartik*	*Male – Female Bartik*	
SW F-Stat	73.71	54.96	34.23	35.84	71.90	50.99
Prob >F	0.000	0.000	0.000	0.000	0.000	0.000

Notes: N=1,796 for Non-Metro CZs and N=1,092 for Metro CZs. See Table 4.1 for list of controls. Standard errors in parentheses, * $p < .10$, ** $p < .05$, *** $p < .01$

by a larger magnitude for own-gender changes in labor demand for women in non-metro areas (a 7.22% versus a 4.05% increase for a 10% increase in female labor demand). This could be due to the types of jobs driving the female Bartik in rural areas. Basic manufacturing and retail contain generally lower-skilled occupations, so marginally attached workers could more easily enter the workforce. I also find that women are more likely to leave the labor force with an increase in male labor demand in non-metro areas. Female LFP drops by 5.64% in response to a 10% increase in job growth for men in non-metro areas; for women in metro areas, the effect is 3.70%. In addition, men enter the labor market at lower rates in non-metro areas in response to job growth (1.14% versus 2.57%). Because the male Bartik instrument is driven by Mining in non-metro areas, it could be the case that higher migration to mining-rich areas creates more competition for local men for the same jobs.

4.2 Housing Values and Rental Prices

If male job growth induces larger effects on adult populations, there should be a corresponding increase in the demand for housing and rents. I find this to be the case and present two non-labor outcomes in Table 4.3: rental prices and housing values. I use two measures of both housing values and rents. The first uses the CZ average for rents and home values, while the second produces a rental and house value premium for each CZ. The second follows Shapiro (2006), Albouy (2009), and Notowidigdo (forthcoming). Using individual-level Census data, the value premium is constructed by regressing the respective log values on controls – such as number of bedrooms and total rooms – and CZ fixed effects.[17] The CZ fixed effect estimated from this regression is a *feature-adjusted* measure of the local area rental and home value premium.

Results using the aggregate Bartik are in line with previous literature (Table 4.3, Panel I.). A 10% increase in total employment increases rents by 4.7% and housing values by 1.3%. The rental price and home value premiums show similar increases, although the magnitudes are not as large (0.51% and 1.06%, respectively).

I decompose the Bartik into it's gender-specific components in Panel II. As expected, male employment growth increases both local area home values and rental prices. A 10% increase in male employment is correlated with a 1.55% increase in rental price premiums and a 1.26% increase in home value premiums. Female employment growth has no significant effect on home value premiums and reduces rental price premiums by a small amount (0.97%). Due to the higher migratory response of males, male job growth makes commuting zones relatively more expensive than female job growth.[18]

4.3 Wages

This section gives the results of changes in local labor demand on wages and the gender wage gap. One issue is that labor demand growth could be con-

[17] See Appendix B for details.

[18] Results for metro and non-metro areas were similar with and are available on request.

Table 4.3: Impact of Employment Growth on Home Values and Rental Prices – All Commuting Zones. Dependent variables: percentage change in rental prices, rental price premium, home values, and home value premium

	A. Rental prices	*B. Rental price premium*	*C. Home values*	*D. Home value premium*
	I. Aggregate Labor Demand Growth			
Δ Total LD	0.469***	0.051***	1.299*	0.106**
	(0.15)	(0.02)	(0.67)	(0.05)
	II. Male – Female Labor Demand Growth			
Δ Male LD	0.872***	0.155***	1.389***	0.126***
	(0.13)	(0.02)	(0.28)	(0.02)
Δ Female LD	-0.361*	-0.097***	-0.006	-0.013
	(0.22)	(0.03)	(0.71)	(0.05)
Mean Outcome	0.162	0.034	0.220	0.018
Level in 1990	$616	5.89	$178,539	9.98

Notes: N=2,888 (722 CZ x 4 time periods). All models include controls. First stage results are omitted, but identical to Table 4.1. Standard errors in parentheses, * $p < .10$, ** $p < .05$, *** $p < .01$

founded with compositional changes in the population, and changes in labor force participation could obscure changes in wages per adult. I construct two measures for changes in wages in this analysis. The first is the average hourly wage per adult not in school (16-64) in each commuting zone. The second follows Shapiro (2006), Albouy (2009), and Notowidigdo (forthcoming). Using individual-level Census data, I regress log wages of employed workers on a set of demographic, industrial, and occupational controls, as well as CZ fixed effects.[19] The CZ fixed effect estimated from this regression is a *composition-adjusted* measure of the local area wage premium. Table 4.4 reports the results on total wages and local area wage premiums estimated for all commuting zones.

For the aggregate Bartik instrument, the results do not reveal any surprising results: in all specifications across gender and metro/non-metro commuting zones, an increase in jobs leads to higher wages (Panel I of Tables 4.4, 4.5,

[19] See Data Appendix B for details.

Table 4.4: Impact of Employment Growth on Wages – All Commuting Zones. Dependent Variables: Average wages and local area wage premiums at the commuting zone level

	A. Avgerage wages			*B. Local wage premium*		
	I. Aggregate Labor Demand Growth					
	All	Male	Female	All	Male	Female
Δ Total LD	0.384***	0.346***	0.377***	0.159***	0.165***	0.166***
	(0.11)	(0.11)	(0.11)	(0.04)	(0.05)	(0.04)
	II. Male – Female Labor Demand Growth					
	All	Male	Female	All	Male	Female
Δ Male LD	0.650***	0.591***	0.395***	0.289***	0.363***	0.182***
	(0.08)	(0.08)	(0.08)	(0.03)	(0.04)	(0.03)
Δ Female LD	-0.234	-0.213	0.002	-0.115*	-0.178***	-0.007
	(0.16)	(0.16)	(0.16)	(0.06)	(0.07)	(0.06)
Mean Dep Var	0.102	0.086	0.161	0.039	0.052	0.030
Level in 1990	$18.99	$21.45	$15.54	2.07	1.94	2.04

Notes: N=2,888 (722 CZ x 4 time periods). All models include controls. First stage results are omitted, but identical to Table 4.1. Standard errors in parentheses, * $p < .10$, ** $p < .05$, *** $p < .01$

and 4.6.) An increase in labor demand by 10% increases the local wage premium for men by 1.65%; for women, the increase is 1.66% (Panel B). However, asymmetries again appear in the decomposed analysis. I find that, on average for all commuting zones, male labor demand growth increases both male and female average wage growth, though at larger magnitudes for men. In the preferred measure (Table 4.4, Panel B, Section II), a 10% increase in male employment corresponds to 3.63% increase in male wages and a 1.82% increase in female wages. If men and women are moving as couples, the migratory response by males should increase the female labor supply (tied female movers) and depress wages for women. However, this is not the case in the results. This could be explained in a few ways. First, if male employment growth is associated with migration responses, assortative mating could bring in women with greater employment prospects. The rise of assortative mating is well documented (see Eika et al. (2019) and Greenwood et al. (2016), for example). Meanwhile, women who are marginally attached at the low end of the distribu-

Table 4.5: Impact of Employment Growth on Wages – Non-Metro Commuting Zones. Dependent Variables: Percentage change in average wages and local area wage premiums at the commuting zone level

	A. Avgerage wages			*B. Local wage premium*		
	I. Aggregate Labor Demand Growth					
	All	Male	Female	All	Male	Female
Δ Total LD	0.390***	0.453***	0.210***	0.154***	0.194***	0.122***
	(0.06)	(0.06)	(0.09)	(0.03)	(0.03)	(0.03)
	II. Male – Female Labor Demand Growth					
	All	Male	Female	All	Male	Female
Δ Male LD	0.515***	0.470***	0.204***	0.193***	0.273***	0.070***
	(0.05)	(0.06)	(0.04)	(0.02)	(0.03)	(0.02)
Δ Female LD	-0.106	0.008	0.015	-0.031	-0.069	0.057
	(0.09)	(0.10)	(0.12)	(0.04)	(0.05)	(0.04)
Mean Dep Var	0.083	0.069	0.145	0.040	0.057	0.028
Level in 1990	$17.60	$19.39	$14.86	2.02	1.94	1.95

Notes: N=1796 (449 CZs x 4 time periods). All models include controls. First stage results are omitted, but identical to Table 4.2, Panel A. Standard errors in parentheses, * $p < .10$, ** $p < .05$, *** $p < .01$

tion could drop out when their spouses (or significant others) experience wage growth. Additionally, because male employment growth increases population responses, the increase in wages could just be compensating differentials for local costs of living accruing to both men and women. This is corroborated by the evidence from housing rents found in the previous section.

These results for male labor demand growth hold when dissaggregated by metro status. However, the wage responses are greater for men in metro areas. A 10% increase in male labor demand increases the local wage premium for men by 2.73% in non-metro areas and 4.69% in metro areas (Tables 4.5 and 4.6, Panel II-B). For women, the wage effect is also relatively lower in non-metro areas in response to a *male* labor demand increase: 0.7% increase in women's wages versus a 3.08% increase in metro areas. This gives more evidence to assortative mating, as the results for men in metro areas are driven

Table 4.6: Impact of Employment Growth on Wages – Metro Commuting Zones. Dependent Variables: Percentage change in average wages and local area wage premiums at the commuting zone level

	A. Avgerage wages			*B. Local wage premium*		
	I. Aggregate Labor Demand Growth					
	All	Male	Female	All	Male	Female
Δ Total LD	0.327***	0.316***	0.267***	0.131***	0.143***	0.118***
	(0.10)	(0.10)	(0.09)	(0.04)	(0.05)	(0.04)
	II. Male – Female Labor Demand Growth					
	All	Male	Female	All	Male	Female
Δ Male LD	0.798***	0.676***	0.685***	0.397***	0.469***	0.308***
	(0.11)	(0.11)	(0.11)	(0.05)	(0.05)	(0.05)
Δ Female LD	-0.396**	-0.297*	-0.352**	-0.227***	-0.279***	-0.160**
	(0.17)	(0.17)	(0.17)	(0.07)	(0.08)	(0.07)
Mean Dep Var	0.105	0.088	0.163	0.039	0.051	0.030
Level in 1990	$23.35	$25.07	$19.73	2.22	2.13	2.16

Notes: N=1092 (273 CZs x 4 time periods). All models include controls. First stage results are omitted, but identical to Table 4.2, Panel B. Standard errors in parentheses, * $p < .10$, ** $p < .05$, *** $p < .01$

by business services — rather than mining — and may require a higher skill set.

The effects of job growth for women on wages is hard to explain. In non-metro areas, there are insignificant and near zero effects on both women's *and* men's wages. However, there are negative effects for both genders in metro areas. For instance, a 10% increase in female jobs is correlated with a 2.79% *decrease* in male wages and a 1.60% *decrease* in female wages (Table 4.6, Panel II-B). This could be due in part to the fact that when women enter occupations dominated by men, those jobs begin paying less even after controlling for education, race, and work experience (Levanon et al., 2009). For both metro and non-metro areas, female employment growth could may pull in marginally attached, lower productivity women and depress local average female wages in the process.

What does this mean for the gender wage gap? Table 4.7 presents the results of the percentage change in the wage gap calculated using average commuting zone wages and disaggregated by metro status. When analyzing all commuting zones, I find that male employment growth increases the gender wage gap more than female employment growth decreases it. A 10% increase in male employment corresponds to a 2.03% increase in the wage gap. The same increase in female employment only decreases the gap by 1.80%. To put this in perspective, if there were a 10% increase in jobs for men in 1990, holding all else constant, the wage gap would increase from 1.39 to 1.42. This would not have been captured at all if the analysis had used only the aggregate Bartik instrument—there is no significant effect on the wage gap and its magnitude is close to zero.

Table 4.7: Impact of Employment Growth on Wages on the Gender Wage Gap by Metro Status. Dependent variable: Percentage change in the gender wage gap

	Change in Wage Gap		
	I. Aggregate Labor Demand Growth		
	All CZs	Non-Metro	Metro
Δ TotalLD	0.011	0.246***	-0.005
	(0.05)	(0.07)	(0.05)
	II. Male – Female Labor Demand Growth		
	All CZs	Non-Metro	Metro
Δ Male LD	0.203***	0.282***	0.180**
	(0.06)	(0.07)	(0.09)
Δ Female LD	-0.180**	-0.031	-0.167*
	(0.08)	(0.11)	(0.09)
Mean Outcome	-0.062	-0.064	-0.062
Level in 1990	1.39	1.43	1.38

Notes: N=2,888 for all CZs, N=1,796 for Non-Metro CZs, and N=1,092 for Metro CZs. See Table 4.1 for list of controls. Standard errors in parentheses, * $p < .10$, ** $p < .05$, *** $p < .01$

These same results hold when disaggregating by metro status, however the gap widens more in response to male job growth in non-metro areas relative to metro areas. In response to a 10% increase in employment for men, the gap increases by 2.82% as opposed to 1.80% in metro areas. In addition, women in non-metro areas experience no change in the wage gap for own-gender growth.

While the closure of the wage gap is stronger in metro areas in response to an increase in female labor demand, it is not necessarily due to improved conditions for women. In fact, the closure of the wage gap in metro areas can be partially explained by the falling wages to men in response to an increase in employment for women.

5 Robustness

I employ several robustness checks of the results. First, I evaluate the sensitivity of results to different sets of controls. I then compare estimates over different specifications for clues to misspecification. The Bartik estimator is the sum of the product of individual initial shares and national growth rates. Used as is, it is a just-identified instrument in the 2SLS estimation. Since over-identification tests provide more formal tests for misspecification, I use the full set of industry shares as instruments in 2SLS to utilize these tests. I compare OLS, 2SLS, 2SLS with a disaggregated Bartik instrument, and the two-step efficient generalized method of moments (GMM) estimators. I compare all specifications with and without controls and observe how much the point estimates change between them.

Goldsmith-Pinkham et al. (2018) find that the Bartik instrument used in the canonical setting (estimating the inverse elasticity of labor supply) produces estimates that vary when using different sets of covariates and that over-identification tests reject the null that all instruments are exogenous. I find the same issues with the aggregate Bartik instrument in this analysis. However, my main analysis in the paper is the gender-specific labor demand growth that include the male and female Bartik instruments in the regression. The robustness checks for this specification feature reassuring results as outlined below.

Table A.10 presents the results of eight different specifications for the regression of total and gender-specific employment growth on total population. This corresponds to the results from Table 4.1, Column A1. The preferred specification reported in the the main body of this paper are from Column 4. Point estimates fluctuate somewhat but are generally similar across specifications.

However, when using the aggregate Bartik instrument, over-identification tests reject the null hypothesis that all instruments are exogenous, which points to misspecification. The regression with both male- and female-specific Bartik instruments performs better across specifications. Here, the over-identification tests fail to reject the null. These results point to the gender-specific Bartik instruments as being a better specification than one with a single, aggregated instrument alone.

Table A.11 presents the results of the different specifications for the regression of total and gender-specific labor demand growth on local area wage premium growth. This corresponds to the results from Table 4.4, Column B1. The same conclusions that were reached in the previous example hold for this case as well. Combined, the small movements in estimates across estimators is reassuring, and the passing of the over-identification tests leads to the conclusion that the gender-specific Bartik regressions are correctly specified. These same conclusions hold for robustness checks across the different specifications and outcomes given in Section 4. I include the two tables of robustness checks discussed above in the appendix.

6 Conclusion

Using commuting zone level data, I examine the relationship between gender-specific local labor demand growth and changes in population, labor force participation, wages, and housing rents in the United States between 1980-2017. I find that men have been more exposed to geographically concentrated shocks to employment, while job growth for women has been evenly dispersed across space. In my analysis, I believe the most important takeaway is that using an aggregate labor demand instrument masks important heterogeneity by gender both in exposure and response to gender-specific job growth. Migratory responses are greater for men, while labor supply responses are greater for women, and these effects are larger in rural areas. Industry sectors comprising most of the identifying variation of a shock vary by both gender and region of analysis.

If policy makers are interested in place-based policy, gender-specific employment growth needs to be considered. Depending on the goal of the policy maker – whether it is to induce migratory responses or to benefit local residents – careful consideration of the underlying gender and industrial composition should play a key role in instituting policy.

An important limitation to this work centers on the use of the gender-specific Bartik instrument to identify changes in labor demand. In future iterations of this paper, I will incorporate restricted use Census microdata that allows me to follow individuals over time and space. Using firm closures and openings, I can observe which gender is more affected by layoffs as well as if local residents or in-migrants are enjoying the benefits of new jobs.

Future work also involves a more detailed analysis of the change in the underlying composition of the labor force in response to gender-specific job growth. Employment shocks may affect human capital investment decisions differently for men and women, and thus change the shares of high-skilled labor relative to low-skilled labor in an area. I also intend to incorporate some of the task-based literature, as individuals may be more equipped to change industries/occupations based on tasks. For example, women in services could possibly transition to other industries more readily males whose industry-specific tasks are not as transferable.

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A Figures and Tables

Figure A.1: Growth rate of industry by year

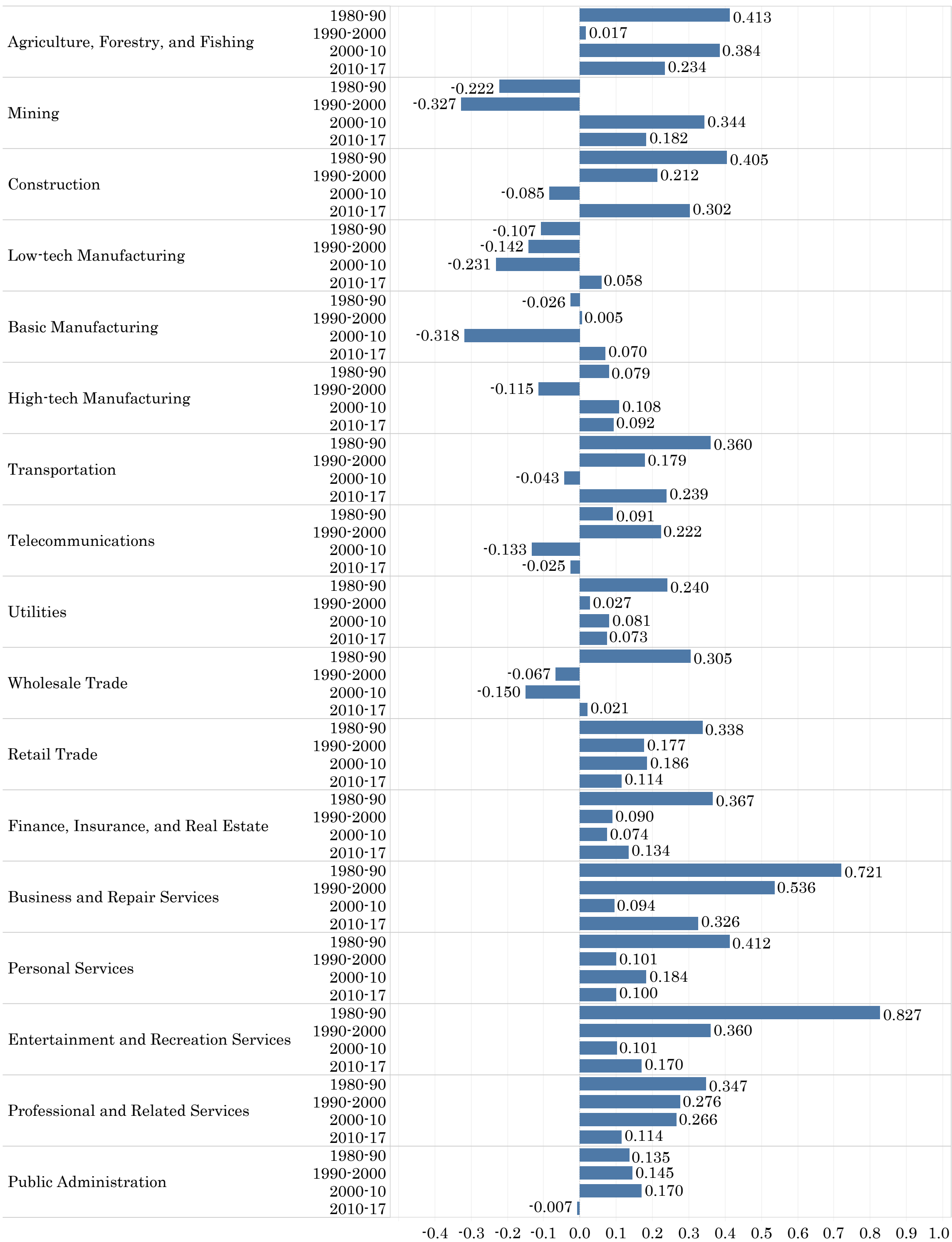


Table A.1: Predicted Labor Demand Growth

	All Commuting Zones			Non-Metro CZs			Metro CZs		
Period	Bartik	Bartik^m	Bartik^f	Bartik	Bartik^m	Bartik^f	Bartik	Bartik^m	Bartik^f
1980-90	0.209	0.178	0.257	0.183	0.149	0.242	0.212	0.182	0.259
	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)
1990-2000	0.118	0.097	0.151	0.095	0.068	0.141	0.121	0.100	0.152
	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)	(0.02)
2000-10	0.053	0.016	0.110	0.071	0.042	0.117	0.051	0.012	0.109
	(0.04)	(0.05)	(0.04)	(0.06)	(0.07)	(0.05)	(0.04)	(0.05)	(0.03)
2010-17	0.109	0.115	0.101	0.108	0.114	0.098	0.110	0.115	0.102
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
All periods	0.122	0.101	0.155	0.114	0.093	0.149	0.124	0.102	0.155
	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)

N=722 for each cell except for all periods result (N=2888). Bartik instruments (predicted labor demand growth) calculated using Equations 18 and 19.

Table A.2: Distribution of Bartik shocks (All CZs)

Table A.3: Distribution of Bartik shocks (Metro CZs)

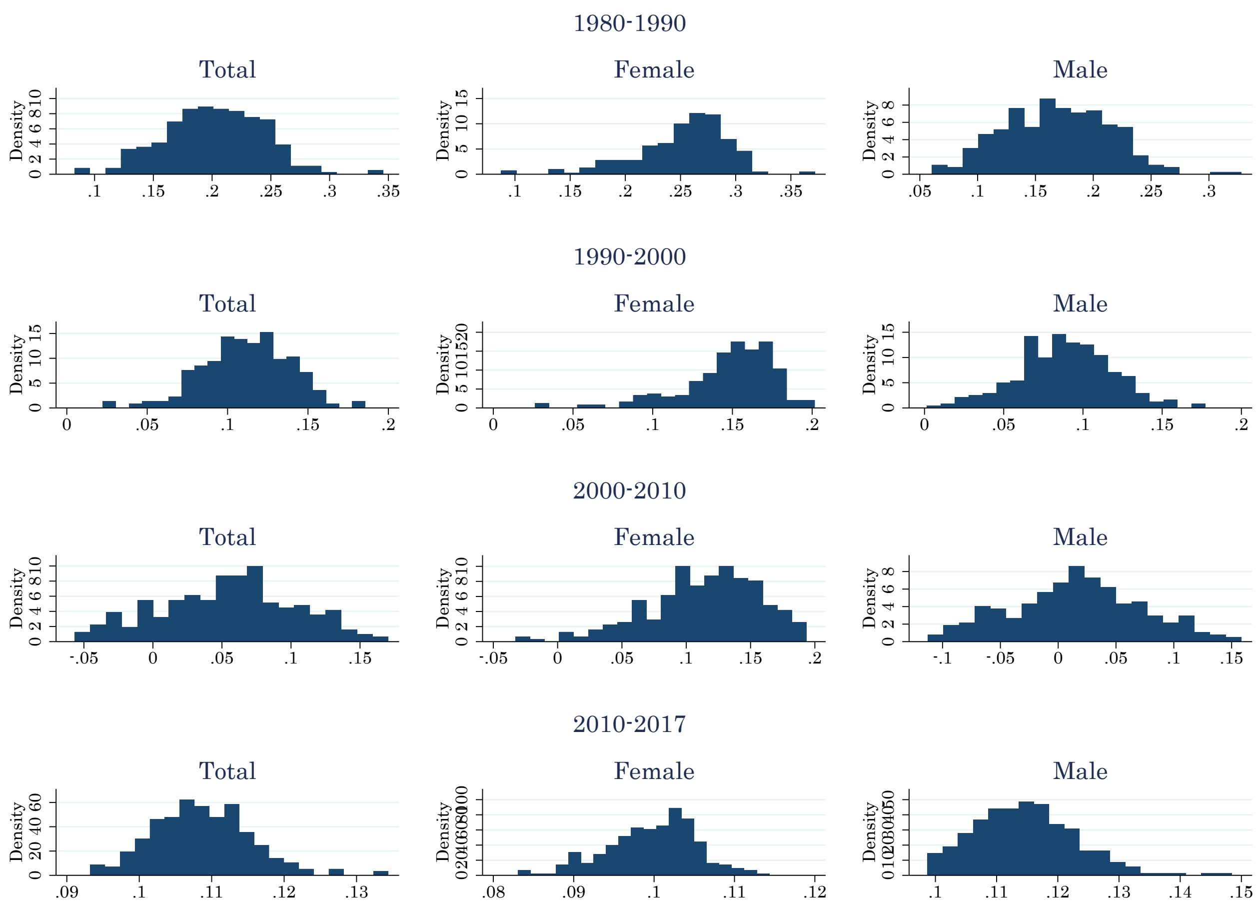


Table A.4: Distribution of Bartik shocks (Non-Metro CZs)

Table A.5: Summary of Rotemberg weights: aggregate Bartik instrument and all CZs

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-0.333	-0.067	0.200
Positive	1.333	0.111	0.800

Panel B: Correlations of Industry Aggregates

	α_k	g_k	β_k	F_k	Var(z_k)
α_k	1				
g_k	-0.148	1			
β_k	0.055	-0.484	1		
F_k	0.630	-0.317	0.109	1	
Var(z_k)	0.369	-0.188	-0.325	0.536	1

Panel C: Variation across years in α_k

	Sum	Mean
1990	0.242	0.014
2000	0.033	0.002
2010	0.714	0.042
2017	0.011	0.001

Panel D: Estimates of β_k for positive and negative weights

	α-weighted Sum	Share of overall β	Mean
Negative	0.385	0.666	-1.452
Positive	0.193	0.334	0.939

Notes: This table reports statistics about the Rotemberg weights. Panel A reports the share and sum of negative weights. Panel B reports correlations between the weights ($\hat{\alpha}_k$), the national component of growth (g_k), the just-identified coefficient estimates ($\hat{\beta}_k$), the first-stage F-statistic of the industry share ($\hat{F}_k$), and the variation in the industry shares across locations(Var(z_k)). Panel C reports variation in the weights across years. Panel D reports statistics about how the values of $\hat{\beta}_k$ vary with the positive and negative Rotemberg weights. For details on the decomposition, see Goldsmith-Pinkham et al. (2018).

Table A.6: Rotemberg details by industry for aggregate Bartik instrument and all CZs

	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	95 % CI	Ind Share
Agriculture, Forestry, and Fishing	-0.035	0.373	0.996	(-0.40,3.00)	1.486
Mining	0.092	-0.841	0.522	(0.40,0.60)	1.401
Construction	0.104	-0.130	0.042	N/A	5.555
Low-Tech Manufacturing	0.079	-0.126	2.648	N/A	6.726
Basic Manufacturing	0.406	-0.497	0.492	(0.20,0.70)	14.575
High-Tech Manufacturing	-0.063	-0.121	0.536	(-0.10,0.80)	3.844
Transportation	0.020	-0.313	20.597	N/A	4.997
Telecommunications	0.003	-1.018	-0.736	N/A	2.488
Utilities	-0.027	-0.087	0.538	(0.20,0.80)	1.816
Wholesale Trade	0.119	-0.210	0.754	(-0.40,1.10)	4.693
Retail Trade	0.028	-0.018	0.620	(0.20,1.00)	11.893
Finance, Insurance, and Real Estate	0.167	0.140	0.643	(-1.90,1.50)	6.421
Business and Repair Services	0.184	0.477	0.989	N/A	2.965
Personal Services	0.033	0.193	0.845	(0.80,1.20)	1.974
Entertainment and Recreation Services	0.099	0.590	1.025	(0.90,4.20)	0.741
Professional and Related Services	-0.047	0.693	-1.567	N/A	19.285
Public Administration	-0.160	-0.039	-0.025	N/A	6.367

Notes: This table reports statistics about the Rotemberg weights. The g_k is the national industry growth rate, $\hat{\beta}_k$ is the coefficient from the just-identified regression, the 95% confidence interval is the weak instrument robust confidence interval using the method from Chernozhukhov and Hansen (2008) over a range from -10 to 10, and Ind Share is the industry share (multiplied by 100 for legibility). For details on the decomposition, see Goldsmith-Pinkham et al. (2018).

Table A.7: Rotemberg Weights by Industry and Gender

Industry	Total	Male	Female
Agriculture, Forestry, and Fishing	-0.035	-0.045	0.001
Mining	0.092	0.112	-0.012
Construction	0.104	**0.172**	-0.004
Low-Tech Manufacturing	0.079	**0.132**	-0.114
Basic Manufacturing	**0.406**	**0.555**	-0.124
High-Tech Manufacturing	-0.063	-0.020	-0.078
Transportation	0.020	0.080	-0.043
Telecommunications	0.003	0.008	-0.019
Utilities	-0.027	-0.018	-0.016
Wholesale Trade	0.119	0.054	0.126
Retail Trade	0.028	-0.039	**0.227**
Finance, Insurance, and Real Estate	**0.167**	0.036	**0.404**
Business and Repair Services	**0.184**	0.103	0.161
Personal Services	0.033	0.002	0.133
Entertainment and Recreation Services	0.099	0.044	0.121
Professional and Related Services	-0.047	-0.077	**0.384**
Public Administration	-0.160	-0.102	-0.149

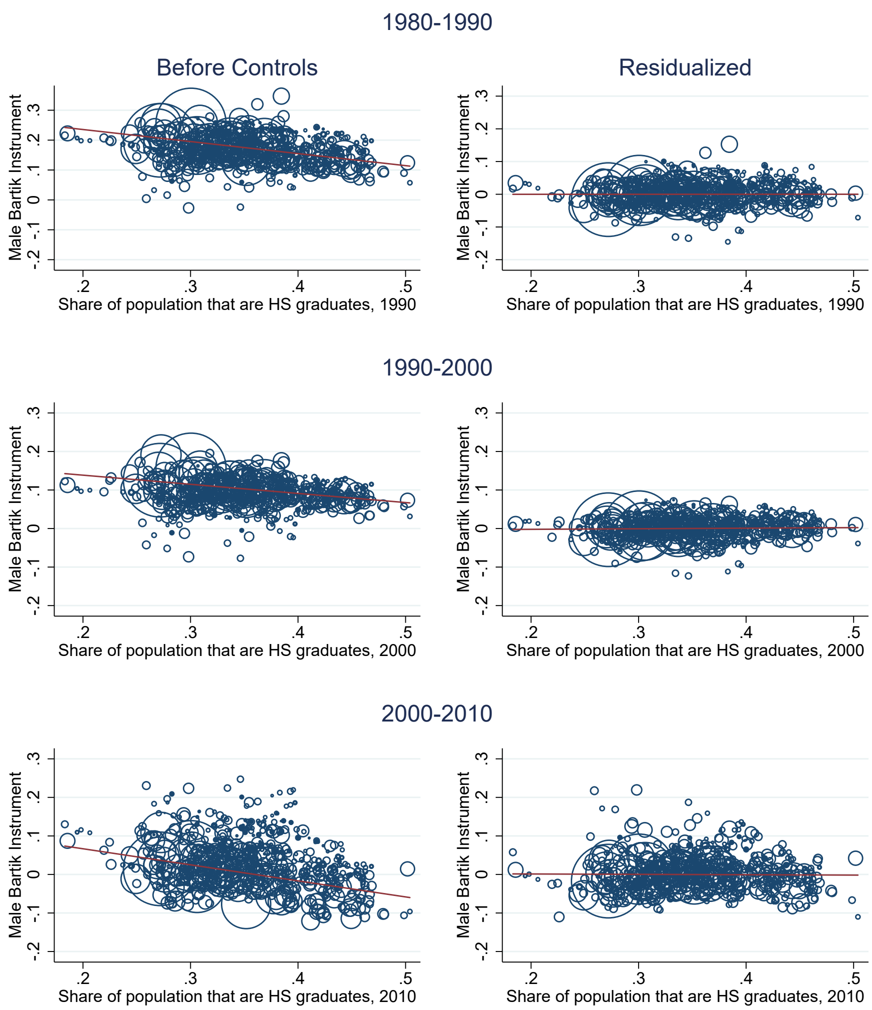
Notes: The Bartik is decomposed into a weighted combination of just-identified estimates based on each instrument. These weights can be interpreted as sensitivity to misspecification elasticities. High weight industries are more sensitive to misspecification. Bolded numbers indicate the top two weights in each gender-group. For details on the decomposition, see Goldsmith-Pinkham et al. (2018). Since this procedure is designed for one endogenous variable, the cross-gender Bartik was used as a control when calculating the gender-specific weights.

Table A.8: Rotemberg Weights by Industry, Gender, and Metro Status

Industry	Metro Total	Metro Male	Metro Female	Non-Metro Total	Non-Metro Male	Non-Metro Female
Agriculture, Forestry, and Fishing	-0.012	-0.026	0.008	-0.153	-0.132	-0.038
Mining	0.037	0.053	-0.012	**0.301**	**0.359**	-0.024
Construction	0.103	**0.174**	-0.006	0.166	**0.217**	0.005
Low-Tech Manufacturing	0.046	0.108	-0.139	-0.081	0.092	-0.273
Basic Manufacturing	**0.447**	**0.619**	-0.169	**0.444**	**0.422**	**0.121**
High-Tech Manufacturing	-0.062	-0.014	-0.083	-0.067	-0.029	-0.066
Transportation	0.014	0.081	-0.051	0.066	0.100	-0.009
Telecommunications	-0.005	0.006	-0.031	0.071	0.037	0.063
Utilities	-0.032	-0.020	-0.017	-0.021	-0.014	-0.011
Wholesale Trade	0.150	0.070	0.150	0.005	-0.010	0.028
Retail Trade	0.033	-0.042	**0.244**	-0.002	-0.045	**0.183**
Finance, Insurance, and Real Estate	**0.204**	0.044	**0.470**	-0.008	-0.012	0.093
Business and Repair Services	**0.199**	**0.108**	0.176	0.080	0.043	0.067
Personal Services	0.044	0.004	0.157	-0.033	-0.013	0.019
Entertainment and Recreation Services	0.113	0.048	0.136	0.026	0.009	0.045
Professional and Related Services	-0.081	-0.092	**0.349**	**0.182**	-0.009	**0.762**
Public Administration	-0.198	-0.119	-0.183	0.023	-0.014	0.033

Notes: The Bartik is decomposed into a weighted combination of just-identified estimates based on each instrument. These weights can be interpreted as sensitivity to misspecification elasticities. High weight industries are more sensitive to misspecification. Bolded numbers indicate the highest three weights in each gender-group. For details on the decomposition, see Goldsmith-Pinkham et al. (2018). Since this procedure is designed for one endogenous variable, the cross-gender Bartik was used as a control when calculating the gender-specific weights.

Figure A.2: Correlation of Male-specific Bartik Instrument and share of population that has a high-school degree



Note: N=722 for each panel. Size of circle represents relative population of individual commuting zones.

Table A.9: Summary Statistics

Outcome Variables	Mean	Std Dev	Min	Max
Percentage change over time of...				
Adult Population	0.106	0.11	-0.493	0.916
Adult Male Population	0.111	0.11	-0.476	0.885
Adult Female Population	0.101	0.11	-0.510	0.946
Labor Force Participation	0.016	0.04	-0.132	0.172
Male Labor Force Participation	-0.014	0.03	-0.154	0.123
Female Labor Force Participation	0.054	0.07	-0.174	0.412
Rent	0.162	0.14	-0.327	1.587
Rental Premium	0.034	0.02	-0.064	0.219
Home Values	0.220	0.27	-0.446	2.619
Home Value Premium	0.018	0.05	-0.125	0.171
Wages	0.102	0.07	-0.238	0.398
Male Wages	0.086	0.06	-0.262	0.436
Female Wages	0.161	0.09	-0.144	0.475
Wage Premium	0.039	0.04	-0.081	0.187
Male Wage Premium	0.052	0.05	-0.090	0.244
Female Wage Premium	0.030	0.03	-0.116	0.159
Gender Wage Gap	-0.062	0.05	-0.273	0.218
Control Variables				
Share that is...				
Female	0.510	0.01	0.450	0.549
White	0.690	0.19	0.038	0.992
Black	0.117	0.10	0	0.696
Hispanic	0.078	0.10	0.001	0.913
Asian	0.044	0.05	0	0.299
Other	0.071	0.07	0	0.655
Less than HS	0.158	0.06	0.031	0.496
College grad	0.252	0.08	0.060	0.495
Veteran	0.094	0.05	0.014	0.230
Foreign Born	0.150	0.13	0.002	0.541
Age 0-14	0.210	0.02	0.130	0.334
Age 15-24	0.133	0.01	0.081	0.265
Age 25-34	0.147	0.02	0.072	0.233
Age 35-44	0.147	0.02	0.086	0.207
Age 45-54	0.130	0.02	0.066	0.183
Age 55-64	0.104	0.02	0.051	0.196
Age $>$ 64	0.130	0.03	0.051	0.334
Average Value				
Number of children per household	0.583	0.10	0.275	1.269
In metro area	0.895	0.31	0	1
Amenity scale rank (1-7)	3.962	1.30	1.333	7

Notes: N=2888. Observations weighted by start-of-period commuting zone population multiplied by 1/10 $\times$ period length.

Table A.10: Robustness Checks – Total Population Growth

	OLS		2SLS (Bartik)		2SLS		GMM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	I. Overall Labor Demand Growth							
Δ Total LD	0.628***	0.618***	0.587***	0.515***	0.632***	0.664***	0.587***	0.515***
	(0.02)	(0.03)	(0.07)	(0.12)	(0.04)	(0.05)	(0.07)	(0.12)
SW F-stat	-	-	31.17	45.48	22.68	18.31	22.68	18.31
p-value	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J-stat	-	-	-	-	36.88	34.04	38.88	34.04
p-value	-	-	-	-	0.002	0.005	0.002	0.054
	II. Male + Female Labor Demand Growth							
Δ Male LD	0.494***	0.419***	0.673***	0.684***	0.835***	0.654***	0.675***	0.684***
	(0.03)	(0.03)	(0.10)	(0.11)	(0.05)	(0.07)	(0.09)	(0.11)
Δ Female LD	0.120**	0.184***	-0.144	-0.132	-0.210***	0.005	-0.110	-0.132
	(0.03)	(0.02)	(0.16)	(0.20)	(0.07)	(0.07)	(0.16)	(0.20)
Male SW F-stat	-	-	102.38	116.83	352.26	76.61	352.26	76.61
p-value	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Female SW F-stat	-	-	30.32	73.95	94.39	41.44	94.39	41.44
p-value	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J-Stat	-	-	-	-	41.665	40.117	41.665	40.117
p-value	-	-	-	-	0.118	0.154	0.118	0.154
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports estimates for total population growth regressed on total, male, and female employment growth (ΔLD). Notes: N=2,888 (722 CZ $\times$ 3 time periods). Controls include start-of-period share of CZ population that is female, black, hispanic, asian, or other, veteran status, foreign born, share in age categories, share of college graduates, average number of children per household, amenity score, and a dummy if the CZ has a metro area. All models include year and Census region fixed effects, and are weighted by 1980 CZ population $\times$ 1/10 of period length. Standard errors in parentheses, * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.11: Robustness Checks – Total Wage Growth

	OLS		2SLS (Bartik)		2SLS		GMM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	I. Overall Labor Demand Growth							
Δ Total LD	0.097***	0.106***	0.128***	0.159***	0.132***	0.157***	0.125***	0.155***
	(0.01)	(0.01)	(0.04)	(0.04)	(0.03)	(0.04)	(0.01)	(0.01)
SW F-stat	-	-	31.17	45.48	22.68	18.31	22.68	18.31
p-value	-	-	0.000	0.001	0.000	0.000	0.000	0.000
Hansen J-stat	-	-	-	-	31.88	24.65	31.88	24.65
p-value	-	-	-	-	0.010	0.076	0.010	0.076
	II. Male + Female Labor Demand Growth							
Δ Male LD	0.130***	0.139***	0.287***	0.289***	0.211***	0.250***	0.216***	0.238***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.01)	(0.01)
Δ Female LD	-0.034**	-0.032*	-0.181***	-0.115*	-0.093***	-0.095***	-0.100***	-0.079***
	(0.02)	(0.02)	(0.04)	(0.06)	(0.03)	(0.04)	(0.01)	(0.01)
Male SW F-stat	-	-	102.38	116.83	352.26	76.61	352.26	76.61
p-value	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Female SW F-stat	-	-	30.32	73.95	94.39	41.44	94.39	41.44
p-value	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J-Stat	-	-	-	-	37.435	33.448	37.435	33.45
p-value	-	-	-	-	0.234	0.397	0.234	0.397
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports estimates for local area wage premium growth regressed on total, male, and female employment growth (ΔLD). Notes: N=2,888 (722 CZ $\times$ 3 time periods). Controls include start-of-period share of CZ population that is female, black, hispanic, asian, or other, veteran status, foreign born, share in age categories, share of college graduates, average number of children per household, amenity score, and a dummy if the CZ has a metro area. All models include year and Census region fixed effects, and are weighted by 1980 CZ population $\times$ 1/10 of period length. Standard errors in parentheses, * $p < .10$, ** $p < .05$, *** $p < .01$

B DATA APPENDIX

The sample of adults used in this analysis consists of all individuals aged 16-64 that are not incarcerated or institutionalized and who lived in one of the 722 commuting zones (CZs) in the sample. Residents of institutional group quarters such as prisons and psychiatric institutions are dropped along with unpaid family workers. The panel of commuting zones comes from the 1980, 1990, and 2000 Census 5% and the 2010 American Community Survey (ACS) individual- and household-level extracts from the Integrated Public-Use Microsaples (IPUMS) database (Ruggles et al., 2018). Public Use Micro Areas (PUMAs) or county groups are matched to commuting zones in the same procedure as Autor et al. (2013).

A subset of this sample is used to distinguish workers and measure labor supply. Workers must have positive and non-missing hours worked and annual income to be included in the measure of predicted employment. Individuals who are self-employed, in the military, or are unpaid family workers are excluded. Labor supply is measured by multiplying weeks worked times usual weekly hours worked. Individual hourly wages are computed by dividing yearly wage and salary income by the product of weeks worked and usual weekly hours worked. Top-coded yearly wage income values are multiplied by 1.5, and hourly wages below the first percentile of the national hourly wage distribution are set to the value of the first percentile (following Autor and Dorn (2009)). The computation of full-time, full-year weekly wages is based on workers who worked for at least 40 weeks and at least 32 hours per week. Wages are inflated to the year 2012 using the Personal Consumption Expenditure Index.

Following Shapiro (2006), Albouy (2009), and Notowidigdo (forthcoming), I construct an estimate of the local area wage premium, log wages of the worker sample are regressed on commuting zone fixed effects, a quadratic in potential experience (age - years of education - 6), 17 industry dummy variables, 5 occupation category dummy variables, and dummy variables for gender, veteran status, marital status, and race. This regression is run each decade separately for male and female workers. The magnitude of the commuting zone fixed effects corresponds to the local area wage premium. All regressions and calculations of local area averages are computed using the Census individual sampling weights.

The rental price and housing value local area premiums are computed in a similar fashion. Following Notowidigdo (forthcoming), the log of rental price or housing value is regressed on a quadratic in the number of bedrooms and the number of rooms and an interaction term between the two. These regressions are also run separately for each decade and use the Census household weights since the housing value and rental price data are reported at the household level. I replace top-coded values using a common ad-hoc technique — based on estimates from Pareto imputations — by replacing top-coded values with a multiple of the top-code threshold. In this case, all households with top-coded rental prices or housing values in a year are assumed to have values at 1.5 times the top-code threshold (Notowidigdo, forthcoming; Autor and Dorn, 2009; Katz and Murphy, 1992).

C Details of the Theoretical Model

This Appendix outlines the derivation and results of the theoretical model.

Using the inverse labor supply functions (Equations 7 and 8), the labor supply gender wage gap is:

$$\frac{W_{Mjt}}{W_{Fjt}} = \left(\frac{1}{1+T_{jt}}\right)\left(\frac{L_{Mjt}}{L_{Fjt}}\right)^{\frac{1}{\gamma}} \tag{20}$$

Combining this with the labor demand wage gap equation in 5, I obtain:

$$\frac{L_{Mjt}}{L_{Fjt}} = \left[(1+T_{jt})\left(\frac{\theta_{Mjt}}{\theta_{Fjt}}\right)\right]^{\frac{\gamma}{1-\rho\gamma}} \tag{21}$$

$$\frac{W_{Mjt}}{W_{Fjt}} = \left(\frac{\theta_{Mjt}}{\theta_{Fjt}}\right)^{\frac{1}{1-\rho\gamma}}\left(\frac{1}{1+T_{jt}}\right)^{\frac{\rho\gamma}{1-\rho\gamma}} \tag{22}$$

I can now write the aggregate labor used by firms in terms of gender employment, productivity, labor force participation costs, and other exogenous parameters. From the original aggregate labor equation used by firms,

$$L_{jt} = (\theta_{Fjt}L_{Fjt}^{\rho} + \theta_{Mjt}L_{Mjt}^{\rho})^{\frac{1}{\rho}}$$

I rewrite this using 21:

$$L_{jt} = L_{Fjt}\left[\theta_{Fjt} + \theta_{Mjt}\left(\left[(1+T_{jt})\left(\frac{\theta_{Mjt}}{\theta_{Fjt}}\right)\right]^{\frac{\rho\gamma}{1-\rho\gamma}}\right)\right]^{\frac{1}{\rho}} \tag{23}$$

$$L_{jt} = L_{Mjt}\left[\theta_{Fjt}\left(\left[(1+T_{jt})\left(\frac{\theta_{Mjt}}{\theta_{Fjt}}\right)\right]^{\frac{-\rho\gamma}{1-\rho\gamma}}\right) + \theta_{Mjt}\right]^{\frac{1}{\rho}} \tag{24}$$

Using Equation 3 for female wages:

$$W_{Fjt} = \alpha A_{jt}L_{jt}^{\alpha-\rho}K_{jt}^{1-\alpha} \times \theta_{Fjt}L_{Fjt}^{\rho-1}$$

I use 23 to derive:

$$W_{Fjt} = \alpha A_{jt}(\Psi_{Fjt})^{\alpha-\rho} K_{jt}^{1-\alpha} \times \theta_{Fjt} L_{Fjt}^{\alpha-1} \tag{25}$$

$$\Psi_{Fjt} = \left[\theta_{Fjt} + \theta_{Mjt}\left(\left[(1+T_{jt})\left(\frac{\theta_{Mjt}}{\theta_{Fjt}}\right)\right]^{\frac{\rho\gamma}{1-\rho\gamma}}\right)\right]^{\frac{1}{\rho}}$$

Using the female inverse labor supply in 7, I find equilibrium employment and wages:

Rents and net average wages in a commuting zone (from Equations 13 and 11) are:

$$R_{jt}^{*} = \left(\beta \frac{\bar{W}_{jt}^{net}}{\bar{H}\left(\frac{1+r_t}{r_t}\right)^{\zeta}} L_{jt}\right)^{\frac{1}{1+\zeta}}$$

$$\bar{W}_{jt}^{net} = \left(\frac{L_{Mjt}}{L_{jt}} W_{Mjt} - \bar{\varphi}_{Mjt}\right) + \left(\frac{L_{Fjt}}{L_{jt}} W_{Fjt} - \bar{\varphi}_{Fjt}\right)$$

where $\bar{W}_{jt}^{net}$ are the average net wages for households in the local area and $\bar{\varphi}_{Gjt}$ is the average participation cost for each gender that sorts into the workforce.

Average participation costs correspond to the expected value for the population of each gender whose wages are weakly larger than the costs ($W_G > \psi_G$). Given the functional form assumption on $F(\varphi_i)$, the average participation costs can be re-written as:

$$\bar{\varphi}_{Fjt} = \left(\frac{\gamma}{\gamma+1}\right)(1+T_t)\left(\left(\frac{W_{Fjt}}{1+T_t}\right)^{\gamma+1} - 1\right) \tag{26}$$

$$\bar{\varphi}_{Mjt} = \left(\frac{\gamma}{\gamma+1}\right)\left({W_{Mjt}}^{\gamma+1} - 1\right) \tag{27}$$

Expected net wages depend on the probability of participating in the labor market in commuting zone j given local wages, and the average costs of participation found in Equations 26 and 27. This yields the expected net labor income for females and males in each commuting zone:

$$E(W^{net}_{Fj}) = \underbrace{\left(\frac{W_{Fjt}}{1+T_t}\right)^{\gamma}}_{\text{P(participating)}} \left[W_{Fjt} - \underbrace{\left(\frac{\gamma(1+T_t)}{\gamma+1}\left(\left(\frac{W_{Fjt}}{1+T_t}\right)^{\gamma+1} - 1\right)\right)}_{\bar{\varphi}_{Fjt}}\right]$$

$$E(W^{net}_{Mj}) = \underbrace{\left(W_{Mjt}\right)^{\gamma}}_{\text{P(participating)}} \left[W_{Mjt} - \underbrace{\left(\frac{\gamma}{\gamma+1}\left(W^{\gamma+1}_{Mjt} - 1\right)\right)}_{\bar{\varphi}_{Mjt}}\right]$$

Under spatial equilibrium, households are indifferent across locations and indirect utility can be written in terms of local amenities, expected net household wages, and number of workers: $V_{jt}(\Lambda_j, E[W^{net}_{jt}], L_{jt}) = \underline{U}$. Using Equations 10 and 13,

$$L_{jt} = \Big(\frac{\xi\Lambda_j}{\underline{U}}\Big)^{\frac{1+\zeta}{\beta}}\Big(E[W^{net}_{jt}]\Big)^{\frac{\zeta+1-\beta}{\beta}}$$

where $\xi = \beta^{\beta}(1-\beta)^{1-\beta}\big(\beta/\bar{H}(\frac{1+r_t}{r_t})^{\zeta}\big)$ and $E[W^{net}_{jt}] = E[W^{net}_{Fjt}] + E[W^{net}_{Mjt}]$.

Using 14 and inserting the terms for the expected net wages of males and females in 15 and 16, I can derive:

$$L_{jt} = \Big(\frac{\xi\Lambda_j}{\underline{U}}\Big)^{\frac{1+\zeta}{\beta}}\Big(E[W^{net}_{Fjt}] + E[W^{net}_{Mjt}]\Big)^{\frac{\zeta+1-\beta}{\beta}} \tag{28}$$

I can re-write this using Equation 22 where male (female) wages are a function of female (male) wages. Then, using Equations 15 and 16, I express 28 that implicitly defines the population in terms of exogenous parameters of the model. This same process is used to construct local housing rents, gender-specific wages, and employment in terms of the exogenous parameters. For further details on a similar model, see Chauvin (2018).