The Incidence of Local Labor Demand Shocks

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Abstract

Low-skill workers are comparatively immobile: when labor demand slumps in a city, low-skill workers are disproportionately likely to remain to face declining wages and employment. This paper estimates the extent to which (falling) housing prices and (rising) social transfers can account for this fact using a spatial equilibrium model. Nonlinear reduced form estimates of the model using U.S. Census data document that positive labor demand shocks increase population more than negative shocks reduce population, this asymmetry is larger for low-skill workers, and such an asymmetry is absent for wages, housing values, and rental prices. GMM estimates of the full model suggest that the comparative immobility of low-skill workers is not due to higher mobility costs per se, but rather a lower incidence of adverse labor demand shocks.

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strictly decreasing, so that the mobility cost of the marginal migrant increases as more workers out-migrate.[14]

To derive the (implicit) labor supply curve for low-skill workers, let $v_i(w^L_{it} + b^L_{it}, p^{\mathcal{H}}_{it})$ be the indirect utility function for the marginal low-skill worker in city i. Spatial equilibrium in the first period requires that the following condition holds for the marginal low-skill migrant in city i:

$$v_i(w^L_{it} + b^L_{it}, p^{\mathcal{H}}_{it}) = v_j(w^L_{jt} + b^L_{jt}, p^h_{jt})\ \forall j \neq i$$

Now consider a shock to θ_i in city i. The shock will cause a wage differential which will encourage costly migration to arbitrage the wage and employment differential, and the price of housing and transfer payments will also adjust as a local general equilibrium response to the shock. Differentiating the above spatial equilibrium condition and applying Roy's Identity results in the following expression:[15]

$$(1 - s^L_b)\Delta w^L_{it} + s^L_b \Delta b^L_{it} - s^L_{\mathcal{H}} \Delta p^{\mathcal{H}}_{it} + c^L(\Delta L_{it}) = 0 \tag{5}$$

where s^L_b $(= b^L/(w^L + b^L))$ is public assistance income as a share of total income. An analogous expression holds for high-income workers (where $s^H_b = 0$):

$$\Delta w^H_{it} - s^H_{\mathcal{H}} \Delta p^{\mathcal{H}}_{it} + c^H(\Delta H_{it}) = 0 \tag{6}$$

[14] Note that this two-period model contains two important simplifications which make it straightforward to study mobility costs. First, following Topel (1986), gross migration will always equal net migration, so that there is only one marginal migrant per worker type in each city. The work of Artuc, Chaudhari, and McLauren (2009) and Chaudhari and McLauren (2007) suggest a tractable way to relax this assumption and allow gross migration flows to exceed net migration flows. Second, the mobility cost function is allowed to be asymmetric, but since this is a two-period model the shape of this function does not depend on the history of past shocks. In a fully dynamic model, the history of past shocks may affect the elasticity of supply of in-migrants and out-migrants.

[15] The full derivation of equation (5) is given below: following a shock to city i, the new spatial equilibrium following the shock will be given by the following expression:

$$\frac{dv_i}{d\log(\theta_i)} + \frac{\partial v}{\partial(w+t)} m(\Delta L_{it}) = 0$$

In words, this means that the change in indirect utility to the marginal migrant must equal that migrant's mobility costs, scaled by the marginal utility of (total) income. The argument ΔL_{it} is the equilibrium change in population in response to the shock; i.e., $d\log(L_{it})/d\log\theta_{\iota t}$, which is used to "pick out" the marginal migrant after the population has changed by ΔL_{it}. Computing the full derivative $dv_i/d\theta_{\iota t}$ and applying Roy's Identity yields equation 5.

Equations (5) and (6) are implicit labor supply curves because net migration is determined by the spatial equilibrium condition for the marginal migrant. In words, the conditions above state that the change in indirect utility in response to changes in wages, transfer payments, and housing prices must equal the mobility costs of the marginal migrants. The ΔL_{it} and ΔH_{it} terms represent the amount of net migration that needs to occur to make these two equations hold.

These two equations highlight the three reasons discussed in the introduction why net migration rates may differ by skill. First, public assistance program benefits are means-tested, so that $s_b^L > s_b^H$. Second, low-skill workers consume a larger fraction of their income on housing $s_{\mathcal{H}}^L > s_{\mathcal{H}}^H$, meaning that housing price declines disproportionately compensate low-skill workers. Finally, the mobility cost functions may differ by skill. If low-skill workers typically face higher mobility costs following a negative shock, then $c^L(x) > c^H(x)\ \forall x < 0$.

2.5 Equilibrium

Following an exogenous shock to local labor demand ($\Delta\theta_{it}$), the new equilibrium of the model is defined by the following conditions:

- Labor demand adjusts so that high-skill and low-skill wages equal marginal products (equations (1) and (2)).
- Transfer payments adjust according to changes in low-skill wages (equation (3)).
- Housing prices adjust so that the change in housing demand equals the change in housing supply (equation (4)).
- Population adjusts so that the marginal high-skill and low-skill migrant is indifferent between staying and leaving (equations (5) and (6)).

Although the nonlinearities in the housing supply curve ($\Delta H^S(\Delta p_{it}^{\mathcal{H}})$) and the mobility cost functions ($c^H(\Delta H_{it})$ and $c^L(\Delta L_{it})$) preclude analytical solutions without particular functional form assumptions, Section A.2 in the Online Appendix derives comparative statics for specific scenarios under the special case of constant returns to scale of production ($\alpha = 1$).

Figure 3 reports results from simulating the model.[16] The figure shows that if population responds asymmetrically, it suggests the existence of a concave housing supply curve and/or the existence of heterogeneous mobility costs. The responsiveness of housing prices isolates the importance of heterogeneous mobility costs, since mobility costs cause immobile workers to bid up the price of housing during negative shocks, causing housing prices to respond asymmetrically. Therefore, the model suggests that it is possible to identify both mobility costs and the shape of the housing supply curve by using information on the joint responses of wages, population, housing prices, and transfer payments to exogenous labor demand shocks.

These simulations motivate the two-part empirical strategy below. First, I will estimate nonlinear reduced form regressions to test for asymmetric responses to labor demand shocks. Second, I will carry out a full estimation of the model to recover the parameters which govern the distribution of mobility costs and the shape of the housing supply curve.

3 Empirical Strategy and Data

As the model makes clear, the reduced form relationships between each of the endogenous variables (Δw^H, Δw^L, ΔH, ΔL, Δp^h, Δt^L) and the labor demand shock $\Delta\theta$ are informative about the shape of housing supply curve and the presence of heterogeneous mobility costs. This motivates the following reduced form estimating equation:

$$\Delta x_{it} = g^x(\Delta\theta_{it}) + \alpha_t + \Delta\varepsilon_{it}$$

where i indexes cities, t indexes time periods, x is one of the endogenous variables above, α_t captures proportional shocks to all cities in a given time period, ε_{it} is an error term, and $g()$ is a function to be estimated. Nonparametric estimates of $g()$ are reported graphically below. In addition to the nonparametric estimates, I also parameterize $g^x(\Delta\theta)$ as $\beta(\Delta\theta) + \delta(\Delta\theta)^2$ which leads to the following baseline reduced form empirical specification that is reported in the tables:

$$\Delta x_{it} = \beta \times \Delta\theta_{it} + \delta \times (\Delta\theta_{it})^2 + \alpha_t + \varepsilon_{it} \tag{7}$$

[16] The details of the simulation are given in Section A.3 in the Online Appendix.

where x is the endogenous variable of interest, β and δ are the coefficients on a quadratic in $\Delta\theta_{it}$, and α_t are year fixed effects. This reduced form specification is estimated by OLS using a proxy for local labor demand (described below). The quadratic specification allows the elasticity of x_{it} with respect to θ_{it} to vary: specifically, the elasticity at $\Delta\theta_{i,t} = 0$ is given by $\hat{\beta}$, while $\hat{\beta} + 2\hat{\delta}\Delta\theta_{it}$ is the elasticity at $\Delta\theta_{it}$. Since the equation is estimated in first differences it implicitly controls for time-invariant differences across geographic areas, while the inclusion of year fixed effects captures any (proportional) changes in x_{it} common to all cities. Formally, the statistical test of $\delta \neq 0$ is sufficient to establish that positive and negative shifts in labor demand of equal magnitude have unequal effects. However, this test is evaluating the null hypothesis of a linear relationship against a specific parametric alternative. Therefore, I will also report nonparametric specification tests which test the null hypothesis of a linear relationship against a nonparametric alternative (Ellison and Ellison, 2000).

Lastly, I also estimate the full model developed above to recover flexible estimates of the mobility cost functions of high-skill and low-skill workers and the housing supply curve parameters. The estimation is a nonlinear, simultaneous equations problem, and it is implemented using a two-step GMM estimator. The details of the GMM procedure are described in more detail below.

3.1 An Omnibus Instrumental Variable for Local Labor Demand

In order to estimate equation (7) above, a valid instrumental variable for local labor demand is needed. I follow the empirical strategy of Bartik (1991) and construct a measure of plausibly exogenous labor demand shocks derived by interacting cross-sectional differences in industrial composition with national changes in industry employment shares.[17] This relative demand index can be used to predict changes in wages and employment. The identifying assumption is that changes in industry shares at the national level are uncorrelated with city-level labor supply shocks and therefore represent plausibly exogenous (demand-induced) variation in metropolitan area employment. This predicted employment variable ($\hat{E}_{it}$) is used to create a predicted change in local area employment ($\Delta\hat{\theta}_{it}$) as follows: $\Delta\hat{\theta}_{i,t} = (\hat{E}_{it} - E_{i,t-\tau})/E_{i,t-\tau}$. This measure is used

[17] See Blanchard and Katz (1992), Bound and Holzer (2000), Autor and Duggan (2002), and Luttmer (2005) for other applications of this instrumental variable.

as a proxy for $\Delta\theta_{it}$.[18]

The key identifying assumption is that this proxy is uncorrelated with unobserved shocks to local labor supply. In this paper a stronger assumption is also needed – specifically, I must assume that $\Delta\theta_{i,t} = X$ and $\Delta\theta_{i,t} = -X$ represent shifts in local labor demand of plausibly equal magnitude. This requirement gives a clear advantage to the Bartik procedure over other identifiable shocks to local labor demand, as this instrumental variable is an *omnibus* measure of changes in local labor demand. By contrast, if one were to use identifiable shifts to labor demand such as movements in oil prices, coal prices, or other natural resource shocks it would require that equal-sized positive and negative price changes represent equal-sized shifts in local labor demand. This may be difficult to justify in natural resource industries that are typically characterized by high amounts of specific capital and/or irreversible investments. An additional benefit of this procedure is that subsets of industries can be excluded when constructing the instrumental variable to verify that the results are not driven by particular sectors, which we investigate in the robustness analysis below.

An important piece of evidence in support of the key identifying assumption is that the distribution of the estimated labor demand shocks is highly symmetric (Appendix Figure A1). This suggests that any estimated asymmetric responses is not being driven (in part) by an underlying asymmetric distribution of shocks.

3.2 Data and Descriptive Statistics

The data sources are briefly described here. The Data Appendix (Online Appendix Section A.1) gives more detail on how the data set was created.

Census Integrated Public Use Microsamples (IPUMS) The basic panel of metropol-

[18] Formally, predicted employment growth is computed as follows:

$$\begin{aligned} \pi_{it} &= \sum_{k=1}^{K} \varphi_{i,k,t-\tau} \left(\frac{\upsilon_{-i,k,t} - \upsilon_{-i,k,t-\tau}}{\upsilon_{-i,k,t-\tau}} \right) \\ \hat{E}_{it} &= (1 + \pi_{i,t}) E_{i,t-\tau} \\ \Delta\hat{\theta}_{it} &= (\hat{E}_{it} - E_{i,t-\tau})/E_{i,t-\tau} \end{aligned}$$

where $\varphi_{i,k,t-\tau}$ is the employment share of industry k in city i and $\upsilon_{-i,k,t}$ is the national employment share of industry k excluding city i.

itan area data comes from the 1980, 1990, and 2000 Census individual-level and household-level extracts from the IPUMS database (Ruggles et al., 2004).[19] The baseline data are limited to individuals and households living in metropolitan areas. The IPUMS data are used to construct estimates of local area wages, employment, population, housing prices, and rental prices in each metropolitan area. The primary advantage of the Census data is the ability to construct city-level measures disaggregated by skill. These data are also used to construct the predicted labor demand instrumental variable by using the industry categories of the individuals in the labor force. See the Data Appendix for remaining details.

Regional Economic Information System (REIS) The metropolitan-area measures of expenditures on public assistance programs are computed by aggregating the county-level aggregate data in the REIS. The REIS contains annual county-level data on total expenditures broken down by transfer program (e.g., food stamps, income maintenance programs, public medical benefits, veterans benefits, SSI benefits). Counties are aggregated into metropolitan areas using the 1990 Metropolitan Statistical Area (MSA) definitions. Because of the difficulty in aggregating counties into MSAs within Alaska and Virginia during this time period, MSAs in these states are dropped from the baseline sample. Though the data are not disaggregated below the county-level, the data are based on government agency reports and are therefore quite reliable. According to recent work by Meyer, Mok, and Sullivan (2009), aggregate expenditure data may be sometimes preferable to individual or household survey data due to substantial underreporting in the latter.[20] All transfer program measures are adjusted per low-skill capita based on the non-college adult population.

Table 1 reports descriptive statistics for the final data set.

[19] The 2007 American Community Survey (ACS) is included as a robustness check. The 1970 Census is not used at all because it identifies only a small subset of the MSAs that appear in later years.

[20] Meyer, Mok, and Sullivan (2009) find substantial underreporting of benefit receipt in a wide range of data sets, including the CPS, PSID, SIPP, and the Consumer Expenditure Survey for a wide range of transfer programs. They also document that the under-reporting is not consistent over time.

4 Results

4.1 Graphical Evidence

Figures 4 and 5 report nonparametric reduced form estimates for the primary dependent variables. In addition to the nonparametric estimates, linear estimates are graphed for comparison. The figures also display bootstrapped (uniform) 95% confidence intervals.[21] The confidence intervals are very wide at the extremes, making it difficult to reject the null hypothesis that the data are described by any linear relationship. However, in some cases the confidence intervals reject the specific linear relationship estimated using a parametric linear model, though this visual test ignores estimation error in the linear model. Consequently, the nonparametric specification tests reported below will be useful in assessing whether the data reject the null hypothesis that the parametric linear model is appropriate.[22]

Overall, across all of the graphs the only clear evidence of an asymmetric response is for employment and population. The population and employment graphs show a convex relationship with the labor demand instrumental variable. By contrast, there is no evidence of a similar asymmetric relationship for housing values, rental prices, or any measure of wages (wage measures are defined below). As shown by the simulated data in Figure 3, these results are consistent with a concave housing supply curve and limited mobility costs. In order to formally test for the existence of an asymmetric response (and measure the magnitude of the asymmetry when it exists), the next subsection reports results from quadratic specifications and nonparametric specification tests.

[21] The bootstrapped confidence intervals are computed based on 10,000 replications, where MSAs are sampled with replacement. In each bootstrap step, an undersmoothed local linear bandwidth is chosen following Hall (1992). That paper reports Monte Carlo results which suggest that undersmoothing produces confidence interval estimates with greater coverage accuracy than confidence intervals obtained by explicit bias correction. The bandwidth of the Epanechnikov kernel used for point estimation is 0.041; the undersmoothed kernel bandwidth is $0.75 \cdot 0.041 = 0.031$.

[22] In all figures, the nonparametric estimates are local linear regressions. The nonparametric reduced form estimates are also constrained to be monotonic following the rearrangement procedure of Chernozhukov, Fernandez-Val, and Galichon (2003). The rearranged estimates are more efficient under the null hypothesis that the true relationship is (weakly) monotonic. In general, the unconstrained nonparametric estimates are very similar.

4.2 Reduced Form Results

This section reports estimates of equation (7) above to investigate the responsiveness of wages, employment, and population to changes in local labor demand. The baseline reduced form estimating equation is reproduced below:

$$\Delta x_{it} = \beta \times \Delta\hat{\theta}_{it} + \delta \times (\Delta\hat{\theta}_{it})^2 + \alpha_t + \Delta\varepsilon_{i,t}$$

The baseline results are reported in Tables 2 through 4. Table 2 presents results for overall population, employment, and wages. Column (1) shows the results for the total population between the ages of 18 and 64.[23] The estimate of β is precise and strongly statistically significant ($p < 0.001$), which verifies that the measure of predicted employment changes strongly predicts actual shifts in local population. The estimate of δ is also economically and statistically significant ($\hat{\delta} = 28.010$, s.e. 7.905). One way to interpret the magnitude of this estimate is to calculate the marginal effect at one standard deviation greater than zero and one standard deviation less than zero; these estimates are -0.152 and 3.757, respectively, and the difference between these estimates is strongly statistically significant ($p < 0.001$).[24] Additionally, a nonparametric specification test strongly rejects the null hypothesis that the relationship is linear in favor of a nonparametric alternative ($p < 0.001$).[25] In other words, the results in this column suggest that positive changes in local labor demand increase population more than negative changes reduce population. The results for employment in column (2) show evidence of a similar convex relationship. The results in column (3) using the percentage point change in the employment-to-population ratio show that not all of the reduction in local employment from an adverse shock comes from net out-migration; there is also a decline in labor force participation.

[23] Results using the population between the ages of 25 and 54 are very similar.

[24] Note that the p-value for the test of whether the marginal effects are the same at one standard deviation above and below zero is exactly the same as the p-value for the test of whether the quadratic term is statistically significantly different from zero.

[25] I use the nonparametric specification test procedure suggested by Ellison and Ellison (2000), which groups the data into "bins" and creates a test statistic that is asymptotically distributed as a standard normal random variable. To my knowledge, there is a not a data-driven procedure to select the proper bin width; therefore, I view the nonparametric specification test as complementary to the quadratic specification. While the nonparametric specification test does not rely on a specific parametric alternative, it is not possible to ensure that I have the right size and power in constructing my statistical tests. In almost all of the results that follow, inference based on the quadratic specification and the nonparametric specification test is similar.

The remaining columns of Table 2 explore the consequences of local labor demand shifts on wages. There are (at least) two difficulties in constructing an appropriate wage measure. The first difficulty is that the labor demand shock may induce compositional changes in the population, so that the change in the average wage will be confounded by composition effects. The second difficulty is that changes in labor force participation reduce income per adult, but would be excluded using a measure of average wages based only on employed workers.

I approach these problems by first presenting two measures of changes in wage income which should represent upper and lower bounds of the true change in income holding characteristics of the workers fixed. The first measure (following Bound and Holzer (2000)) is the total wage income per 18-64 adult. This measure will account for demand-induced changes in labor force participation but will also include compositional changes. The results are in column (4) and show a large effect of local labor demand on wages ($\hat{\beta} = 0.959$, s.e. 0.137). The second measure (following Shapiro (2003) and Albouy (2009a, 2009b)) uses the individual-level census data and regresses log wages of employed workers on a large set of controls and MSA fixed effects (see Data Appendix for details). The MSA fixed effect estimated from this regression is a composition-adjusted measure of the wage premium which I define as the "residualized wage".[26] The results in column (5) using this measure show a much smaller wage response ($\hat{\beta} = 0.353$, s.e. 0.086). However, this second measure does not account for changes in labor force participation. Assuming that at least some of the observed change in labor force participation is involuntary, then this measure will understate the total effect of the demand shock. To address this concern, I take the residualized wage measure and multiply it by the observed labor force participation rate.[27] I call this the "adjusted wage" and use this as the preferred wage measure. This measure accounts for both compositional changes in the labor force in response to the shock as well as changes in labor force participation, and therefore essentially assumes that reservation wages are negligible. Consequently, I expect this measure to provide an overestimate of mobility costs when I ultimately estimate the full model via GMM. As a way of bounding the estimated

[26] This measure is similar to the local wage premiums calculated in Shapiro (2003) and Albouy (2009a, 2009b). This measure does not control for unobservable changes in the composition of labor force. If unobservable changes in composition of labor force move in the same direction as observable changes, then the measured response of wages will be upward biased, and estimates of mobility costs will be conservative.

[27] Note that when I present results by skill below, I use the labor force participation rate in the given skill group to adjust the residualized wage measure.

magnitude of mobility costs, I also report GMM estimates which use the residualized wage instead of the adjusted wage. The residualized wage will give a lower bound on the estimated magnitude of mobility costs, as it assumes reservation wages are approximately equal to accepted wages for all employed workers.

As expected, the magnitude of the effect of local labor demand for adjusted wages lies in between the other two wage measures ($\hat{\beta} = 0.520$, s.e. 0.109). Since the magnitude of changes in labor force participation is modest, the estimates for adjusted wages are closer to the estimates for residualized wages than the estimates using the per capita income measure. Regardless of the measure of wages used, however, the important conclusion that emerges from columns (4) through (6) is that there is no evidence of an asymmetric response of wages to shifts in local labor demand in any of the wage measures. It is only population and local employment which respond asymmetrically.

Table 3 reports results on population, employment and wages separately for high-skill and low-skill workers. I define low-skill workers as those without a college degree, and high-skill workers as those with at least a college degree. The patterns in Table 2 are reproduced when looking separately within each skill group: population and employment respond asymmetrically, and there is no evidence of a similar asymmetric response for either high-skill or low-skill wages. Furthermore, the magnitude of the wage effects are similar across high-skill and low-skill workers, consistent with the assumption that the labor demand shifts are factor-neutral.[28] Additionally, columns (5) and (6) show suggestive evidence that the skill composition of the adult population and labor force also responds asymmetrically. In other words, negative shocks reduce college share of adult population more than positive shocks increase college share. I emphasize that this asymmetric response is not as robust as the estimated asymmetric responses for population and employment for each skill group. As the simulations in Figure 3 makes clear, when an asymmetric population responses arises from either a concave housing supply curve or heterogeneous costs of out-migration, there is (at most) a small asymmetric responses in the high-skill population share.

Next, Table 4 looks at three important non-labor outcomes: real estate rental prices, housing

[28] Results from stacked regressions do not reject the null hypothesis that the average wage response for high-skill workers is the same as the average wage response for low-skill workers ($p = 0.523$).

values, and aggregate expenditures on public assistance programs. The measures of average rental prices and housing values are purged of observable changes in the quality of the housing stock following a similar procedure to the one used to create the residualized wage measure (see Data Appendix for details). Column (1) in Table 4 reports results for rental prices, which respond strongly to local labor demand. The results for housing values in column (2) are similar in magnitude, though somewhat less precise. As with the wage results, there is no evidence of an asymmetric response in either column; the estimates of δ are statistically insignificant and at most modest in magnitude, and the nonparametric specification tests fail to reject the parametric (linear) model in both columns.[29] Appendix Table A2 reports similar results using the unconditional average rental prices and average housing values, as well as results using the repeated-sales housing price index (HPI) published by the Federal Housing Finance Agency (FHFA), formerly the Office of Federal Housing Enterprise Oversight (OFHEO). Consistent with the results in Table 4, there is no evidence of an asymmetric response in any of these alternative specifications.

Lastly, column (3) reports estimates using aggregate expenditures on Food Stamps and Income Maintenance Programs. The results show that expenditures on these programs respond strongly to local labor market conditions. The estimated magnitude of the response is large ($\hat{\beta} = -2.367$) and implies that a 1% decline in local labor demand increases aggregate expenditures on these two programs by 2.4%. Though the quadratic term is marginally significant ($p = 0.074$), the nonparametric test does not reject the linear model ($p = 0.241$), suggesting that the nonlinear relationship estimated in the quadratic specification is not robust.[30]

A setting in which population and employment respond asymmetrically to positive and negative labor demand shocks while wages, rental prices, and housing values respond symmetrically is consistent with the model simulation where mobility costs are limited and the housing supply curve is concave. Before moving beyond this qualitative conclusion to quantitative estimates of mobility costs and housing supply curve parameters, I next document that these reduced

[29] Additionally, results from stacked regressions reject that the quadratic terms are the same for population and rental prices ($p = 0.0004$) and reject that the quadratic terms are the same for population and housing values ($p = 0.001$).

[30] Appendix Table A3 reports estimates for various other transfer programs, including Medicare, Disability Benefits, SSI, and Veterans Benefits, and the results are qualitatively similar. I focus on Food Stamps and Income Maintenance income because these programs are explicitly designed to smooth consumption.

form results are not driven by unobserved trends, outliers, sample selection, or heterogeneous industry-specific effects. After that, I conclude by estimating the full model above using a nonlinear GMM estimator.

5 Robustness

5.1 Industry Trends

The main results in Table 2 emphasize the importance of asymmetric employment and population responses to local labor demand shocks, and the absence of a similar asymmetric response for wages, housing prices, and transfer payments. The key identifying assumption in interpreting these results is that equally-sized positive and negative predicted changes in local employment represent shifts in local labor demand of plausibly equal magnitude. Because the predicted changes are formed by interacting cross-sectional variation in industrial composition with national changes in industry shares, an obvious concern is that qualitatively different industries are declining and expanding. If these industries would not be expected to have otherwise identical responses to shifts in local labor demand (perhaps because of differences in relative demand for high-skill labor, the amount of specific human capital in the industry, or the ability of firms in the industry to respond and adjust to shocks), then this would cast doubt on the interpretation of the results as tracing out an asymmetric local labor supply curve.

To investigate this concern, I categorize industries based on their decadal changes in total national employment. Industries are grouped into one of four categories:

1. *Persistently expanding/declining industries.* Industries where employment either increased in every decade or decreased in every decade.

2. *Stable industries.* Industries where employment did not increase or decrease more than 20% in any of the decades.[31]

3. *Volatile industries.* Industries that experienced employment growth of more than 20% *and* decreases of more than 20% during the sample period.

[31] If industries are classified as both persistently expanding/declining and stable, I categorize the industry as stable. This definition and the cutoff of 20% were chosen to give roughly equal-sized categories. Results are similar with nearby cutoffs.

4. *Other industries.* Industries not otherwise categorized.

The top twenty industries according to average national employment share in each of these categories are listed in Appendix Table A1. The industries in each of the categories conform to expectations given the secular industry trends during this time period. Persistently expanding industries are concentrated in services, health care, data processing, and leisure goods, while persistently contracting industries are in apparel, publishing, manufacturing, and tobacco. Volatile industries include natural resource industries such as oil and gas extraction as well as defense industries. I begin by constructing predicted employment excluding variation in national employment shares for industries that are persistently expanding or persistently declining.[32] The resulting relative demand index is purged of any variation caused by secular trends in health care, services, and manufacturing. Table 5 reports results from estimating equation (7) using this alternative measure of predicted employment as an instrumental variable for local labor demand. Panel A reports results with the change in adult population as the dependent variable. Column (1) reproduces the results from column (1) in Table 2 for comparison. Column (2) reports results using the predicted employment measure that does not use any variation from industries which are persistently expanding or persistently declining. The point estimates in column (2) are fairly similar to the baseline estimates reproduced in column (1). Columns (3) through (5) report results excluding each of the other industry categories when constructing predicted employment, and the results are also quite similar to the baseline results in column (1). The correlation between the labor demand instrument used in columns (2) and (5) is 0.48, suggesting that the similarity across columns is not simply a mechanical consequence of the different instruments exploiting similar sources of variation. Moreover, while previous research has highlighted the high correlation between this labor demand instrument and the share of employment in manufacturing (Bound and Holzer 2000), the correlation between the instrument in column (2) and the share of adult population employed in manufacturing is only 0.16. Therefore, I interpret these results as suggesting that the estimated asymmetric population response

[32] Formally, predicted employment growth is computed by using only the subset of industries which pass a given filter:

$$\pi'_{i,t} = \sum_{k \in K' \subset K} \varphi_{i,k,t-\tau} \left(\frac{\upsilon_{-i,k,t} - \upsilon_{-i,k,t-\tau}}{\upsilon_{-i,k,t-\tau}} \right)$$

where K is the set of all industries and K' is the set of industries which pass the filter.

is not primarily due to unobserved, heterogeneous, industry-specific trends or effects.

A related concern is that because of the way that the IPUMS creates consistent industry codes across time, there are "catch-all" industry codes that collect industries which are not otherwise categorized. I label an industry code a catch-all industry code if it contains the word "miscellaneous" or contains the suffix "not elsewhere categorized." These catch-all industry codes make up roughly 10% of the industry codes. These catch-all categories may represent different collections of industries in different decades, which may bias the main estimates. To investigate this concern, I create an alternative measure of predicted employment which does not use any variation in national employment shares of these industries. The estimates using this predicted employment measure are reported in column (6) and are similar to the results in column (1), suggesting that there is no significant bias from including these catch-all categories.

Panels B and C of Table 5 report results which repeat this exercise using adjusted wages and rental prices as the dependent variables, respectively. Consistent with the baseline results in Tables 2 and 4, none of the estimates in any of the columns show evidence of an asymmetric relationship between adjusted wages or rental prices and labor demand.[33]

5.2 Alternative Specifications

I next turn to an investigation of the robustness of the main results by reporting alternative specifications which vary the sample definition and the set of time-varying controls used. The purpose of these specifications is primarily to investigate the possibility of sample selection bias and the potential bias from unobserved trends that are correlated with shifts in local labor demand. As with Table 5, Table 6 reports results using population, adjusted wages, and rental prices (respectively) as the dependent variables in each of the panels. All columns report results from estimating variants of equation (7). In all panels, column (1) reports the baseline results for comparison. Column (2) reports results from adding data on the 2000-2007 changes.[34] Column (3) creates "pseudo-MSAs" by grouping together all individuals in a state who are not in an MSA.

[33] Interestingly, the magnitude of the (linear) response of adjusted wages and rental prices to local labor demand varies somewhat depending on the industries used to generate predicted changes in employment, suggesting that the strength of the proxy for local labor demand may vary depending on the set of industries used to generate the proxy.

[34] The 2000-2007 changes are translated into implied decadal changes by first calculating annual percentage changes.

Column (4) reports long-difference results (using the 1980-2000 change) rather than the stacked decadal changes as in the baseline specification. Columns (5) and (6) report results including alternative sets of geographic and time fixed effects. Column (5) includes region fixed effects for each of the nine census regions which control for region-specific linear time trends, while column (6) includes controls for MSA-specific linear time trends. Column (7) reports results which test for the importance of outliers. This column drops the 5% of the data with the largest magnitude changes in local labor demand. Finally, column (8) uses the County Business Patterns (CBP) data set to construct the local labor demand instrument rather than using Census data (see Data Appendix for details). The CBP data contain finer industry categories, which in principle could reduce measurement error, but there are two primary drawbacks: first, there is a high rate of suppressed data at the county-by-industry level, and, second, the county-level data must be aggregated.

Panel A of Table 6 reports results using population as the dependent variable. Across all of the columns, the point estimates are very similar to the baseline specification in column (1). The results in column (6) which include MSA-specific linear time trends show a substantial loss of precision, but the point estimates remain stable. The results in column (7) show that the estimated asymmetric response is robust to dropping outlying observations, suggesting that the convex population response is not primarily driven by outliers. The results in column (8) show the results are similar using CBP data to construct the labor demand instrument.

Panels B and C of Table 6 report results using adjusted wages and rental prices (respectively) as the dependent variables. The estimates of δ are never statistically significant at conventional levels, nor are even consistently the same sign across columns. In other words, there is no consistent evidence of an asymmetric response of adjusted wages or rental prices to local labor demand shocks.

Lastly, Appendix Table A4 reports specifications which drop each one (of nine) census regions. This table confirms that the results do not appear to be driven by any particular region.

In summary, the reduced form patterns of a significant asymmetric response of population and employment to changes in local labor demand appear robust and contrast sharply with a lack of similar asymmetric responses for wages, housing values, and rental prices.

6 GMM Estimates

The reduced form results presented above directly test for the existence of asymmetric responses of wages, population, employment, and housing prices to symmetric labor demand shocks. While revealing, these results do not estimate any of the economic parameters in the theoretical model and are therefore not quantitatively informative about the distribution of mobility costs by skill and the actual incidence of labor demand shocks. This section reports results from a joint estimation of the full model using a nonlinear, simultaneous equations GMM estimator. The econometric setup follows from the theoretical model presented above and imposes moment conditions which can be used to identify the parameters of interest. In particular, the GMM estimator can recover flexible estimates of the housing supply curve and mobility cost functions for high-skill and low-skill workers. These estimates can be used to assess the relative importance of housing expenditures, transfer payments, and mobility costs in generating the observed migration patterns in the data. Additionally, because I parameterize the model so that there are more moment conditions than (remaining) parameters to estimate, the GMM estimator admits a chi-squared overidentification test of the full model.

To implement the GMM estimator, the following equations (derived from equations (1) through (6) in the model above) are used:

$$\begin{aligned}
\Delta e_{it}^{wH} &= \Delta w_{it}^{H} - \left(\Delta\theta_{it} + ((\rho-1) + (\alpha-\rho)(\pi))\,\Delta H_{it} + (\alpha-\rho)(1-\pi)\Delta L_{it}\right)\\
\Delta e_{it}^{wL} &= \Delta w_{it}^{L} - \left(\Delta\theta_{it} + ((\rho-1) + (\alpha-\rho)(1-\pi))\Delta L_{it} + (\alpha-\rho)(\pi)\Delta H_{it}\right)\\
\Delta e_{it}^{t} &= \Delta t_{it}^{L} - \Psi\Delta w_{it}^{L}\\
\Delta e_{it}^{h} &= \Delta p_{it}^{\mathcal{H}} + \Delta H^{s}(\Delta p_{it}^{\mathcal{H}}) - \left(\nu(\Delta w_{it}^{H} + \Delta H_{it}) + (1-\nu)((1-s_{b}^{L})\Delta w_{it}^{L} + s_{b}^{L}\Delta t_{it}^{L} + \Delta L_{it})\right)\\
\Delta e_{it}^{H} &= \Delta w_{it}^{H} - s_{\mathcal{H}}^{H}\Delta p_{it}^{\mathcal{H}} + c^{H}(\Delta H_{it})\\
\Delta e_{it}^{L} &= (1-s_{b}^{L})\Delta w_{it}^{L} + s_{b}^{L}\Delta t_{it}^{L} - s_{\mathcal{H}}^{L}\Delta p_{it}^{\mathcal{H}} + c^{L}(\Delta L_{it})
\end{aligned}$$

where i indexes cities, t indexes time, and Δe_{it}^{j} represent error terms uncorrelated with shifts in labor demand.[35] These equations jointly solve the local general equilibrium problem of

[35] Each of these equations can be derived formally by including error terms which proportionally shift production, housing demand, housing supply, transfer payments, and indirect utility. For example, re-define the

how wages, employment, housing prices, and transfer payments respond to an exogenous labor demand shift $\Delta\theta_{it}$. The six endogenous variables are the following: $\Delta p^{\mathcal{H}}_{it}$, Δw^{H}_{it}, Δw^{L}_{it}, ΔH_{it}, ΔL_{it}, and Δb^{L}_{it}. Note that the error terms are allowed to be freely correlated with each other, which gives rise to simultaneity bias that the GMM estimator is intended to address. The unknowns in the model are the following parameters and functions:

- Transfer income and housing expenditure shares (s^{L}_{b}, $s^{L}_{\mathcal{H}}$, $s^{H}_{\mathcal{H}}$)
- Aggregate share parameters (μ, ν)
- Labor demand parameters (α, ρ, π, ζ)
- Transfer payment elasticity (Ψ)
- Mobility cost functions ($c^{L}(\cdot)$ and $c^{H}(\cdot)$)
- Housing supply function ($\Delta H^{s}(\cdot)$)

In order to reduce the number of parameters to estimate, I first impose values of s^{L}_{b}, $s^{L}_{\mathcal{H}}$, $s^{H}_{\mathcal{H}}$ based on external information. I compute $s^{L}_{b} = 0.05$ by dividing aggregate expenditures on Food Stamps and Income Maintenance Programs by the sum of these expenditures and aggregate low-skill wage income. For the housing expenditure shares, I use $s^{L}_{\mathcal{H}} = 0.34$ for non-college households and $s^{H}_{\mathcal{H}} = 0.30$ for college-educated households based on the data presented in Section 2.[36]

For the labor demand curve, I compute $\pi = 0.37$ based on average wages for high-skill and low-skill workers and average share of high-skill workers in the adult population. I compute the wage premium (ζ) as 1.75, which is the average wages of college-educated workers divided by the average wages of non-college workers. I next compute the average share (over this time period) of college-educated workers in the labor force (μ) as 0.25. Using the formula for π

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equilibrium condition for transfer payments as follows: $t^{L}_{it} = e^{t}_{it} \cdot \bar{T}^{L}\left(w^{L}_{it}\right)^{\Psi^{L}}$, where e^{t}_{it} is a random variable which represents unobservable shocks to transfer payment expenditures (and $E[e^{t}] = 1$). Totally differentiating this condition gives the following expression: $\Delta t^{L}_{it} = \Psi^{L}\left(\Delta w^{L}_{it}\right) + \Delta e^{t}_{it}$, which is the equation used in the GMM estimation.

[36] Average household income is \$82,439 for high-skill households in the baseline sample and is \$48,456 for low-skill households. Assuming $s^{H}_{\mathcal{H}} = 0.30$ for high-skill households and income elasticity of 0.8, then $s^{L}_{\mathcal{H}} = 0.34$ for low-skill households.

in Section 2, this gives $\pi = 0.37$. I compute $\nu = 0.34$ based on the average wages, the skill share, and the housing expenditure shares from above.[37] I choose $\rho = 0.29$ based on Katz and Murphy (1992).[38] This leaves the returns to scale parameter (α) to be estimated. Although this parameter will be estimated from functional form assumptions, it is still useful to include the two moments of the labor demand curve to check the overall fit of the model.[39] This means that misspecification in the functional form of labor demand equation will caused bias estimates in all of the parameters when estimating the entire system of equations. Therefore, I also report results below which drop the labor demand moments.[40]

Finally, I choose the following functional forms for the mobility cost functions and housing supply elasticity:

$$c^j(x) = \frac{\sigma^j(\exp(\beta^j x) - 1)}{\beta^j} \quad j \in \{L, H\}$$
$$\Delta\mathcal{H}^s(x) = \frac{\sigma^h(\exp(\beta^h x) - 1)}{\beta^h}$$

These functions are the exponential transformations suggested by Manly (1976), which represent Box-Cox transformations of exponentiated variables and are defined so that if $\beta^j = 0$, then the functions simplify to $\sigma^j x$. These functions are flexible enough to accommodate interesting curvature with only two parameters, and they are everywhere monotonic and have continuous first derivatives, which greatly simplifies the computation. Ultimately, there are eight remaining parameters to estimate $\{\sigma^h, \beta^h, \sigma^L, \beta^L, \sigma^H, \beta^H, \Psi, \alpha\}$: two housing supply curve parameters (σ^h, β^h), two low-skill mobility cost parameters (σ^L, β^L), two high-skill mobility cost parameters

[37] The aggregate housing demand share parameter is computed using given by $\nu = \mu\zeta s^H_{\mathcal{H}}/(\mu\zeta s^H_{\mathcal{H}} + (1-\mu)s^L_{\mathcal{H}})$.

[38] Katz and Murphy (1992) estimate the elasticity of substitution between high-skill and low-skill labor ($\sigma_{H,L}$) to be 1.4. This gives $\rho = 1 - 1/\sigma_{H,L} = 0.29$.

[39] Since the instrumental variable shifts the labor demand curve, parameters of the labor demand curve itself are identified from functional form assumptions.

[40] Because the labor demand instrument is measured with error, when using it in the GMM estimation, I rescale it by regressing adjusted wages on the instrument and scale the instrument so that this regression with the rescaled instrument would give a coefficient of 1.0. A more rigorous alternative is to modify the labor demand moments to include an additional parameter (κ) as follows:

$$\Delta e^{wH}_{it} = \Delta w^H_{it} - (\kappa\Delta\theta_{it} + ((\rho - 1) + (\alpha - \rho)(\pi))\,\Delta H_{it} + (\alpha - \rho)(1 - \pi)\Delta L_{it})$$
$$\Delta e^{wL}_{it} = \Delta w^L_{it} - (\kappa\Delta\theta_{it} + ((\rho - 1) + (\alpha - \rho)(1 - \pi))\Delta L_{it} + (\alpha - \rho)(\pi)\Delta H_{it})$$

This procedure yields very similar results.

(σ^H, β^H), the responsiveness of transfer payments to low-skill wages (Ψ), and the returns to scale parameter (α).

The resulting GMM estimator solves a nonlinear, simultaneous equations problem, so in order to estimate the nonlinear parameters I need to take nonlinear functions of the instrumental variable ($\Delta\theta$) to achieve identification. I use $\Delta\theta$, $(\Delta\theta)^2$, $(\Delta\theta)^3$, $(\Delta\theta)^4$, and $(\Delta\theta)^5$ as instrumental variables.[41] This results in 30 moment conditions (the five polynomial functions of the instrument $\times$ the six error terms). The full model is estimated using a standard two-step GMM procedure (see Section A.5 of the Online Appendix for details of this procedure).

The GMM estimates are presented in Table 7. The first row presents the preferred specification using the external estimates discussed above. Columns (1) and (2) report estimates of the housing supply curve. The estimates suggest that the housing supply curve is concave ($\beta^h = 6.306$, s.e. 1.774). One way to interpret the housing supply coefficients is to compute the increase in housing supply when housing prices exogenously rise by 20% (24.1%) and compare it to the decrease in housing supply when housing prices decline by 20% (-6.8%). In other words, the magnitude of housing supply response is about four times larger for an increase in housing prices than for an equal-sized decrease in housing prices.

The estimates of the mobility cost function parameters (columns (3) through (6)) give no evidence of an asymmetric mobility cost function for either high-skill or low-skill workers; the estimates suggest that the mobility cost functions are approximately linear. The point estimates for σ^L and σ^H are precisely estimated and statistically significantly different from zero, suggesting the existence of non-negligible mobility costs. To get a sense of the magnitudes, the point estimates imply that the 10th percentile of mobility costs in a city (i.e., the marginal migrant after 10% of the population has out-migrated following a negative shock) is roughly 17.4% of annual income for high-skill workers and 17.0% of annual income for low-skill workers.[42] In other words, despite the fact that low-skill workers are disproportionately likely to remain in

[41] In principle, only the quadratic term is needed ot identify the parameters of the model. Adding additional polynomial terms increases statistic power at the cost of introducing bias (either because the orthogonality assumption is not satisfied at higher moments or the additional polynomial introduces a weak instruments problem). In the absence of a principled procedure to select instruments, I added additional polynomial terms as long as they gave substantial additional statistical precision.

[42] I assume the marginal migrant has 25 years of working life remaining and thus must trade off remaining to face permanently lower wage and employment opportunities against paying the one-time mobility cost to out-migrate and avoid the adverse wage and employment consequences.

declining cities following negative shocks, the point estimates imply that high-skill workers have very similar mobility costs as a fraction of income (and therefore that low-skill workers have lower absolute mobility costs on average). Column (7) reports the estimated transfer payment elasticity, which is quantitatively large and precisely estimated; the coefficient implies that a 1% decline in low-skill wages increases transfer payment expenditures by 3.8% (s.e. 0.5%). Column (8) reports estimates of the returns to scale parameter ($\alpha = 1.038$, s.e. 0.025), which suggests that returns to scale are approximately constant and is consistent with the reduced form results, which found no evidence of an asymmetric response of wages.[43] This is important because increasing returns to scale are not consistent with the equilibrium conditions of the model. The p-value in column (8) reports results of testing $\alpha = 1$; in our baseline model, we are not able to reject the null of constant returns to scale ($p = 0.129$). Finally, the results in column (10) show that the overidentification test does not reject the null hypothesis that the deviations of the empirical moments from the model are due to chance ($p = 0.515$).

The remainder of Table 7 reports estimates of the full model under alternative economic assumptions. The second row reports estimates assuming that both housing expenditure share and public assistance expenditures do not differ by skill and are negligible (i.e., $s^H_{\mathcal{H}} = s^L_{\mathcal{H}} = 10^{-6}$ and $s^H_b = s^L_b = 10^{-6}$). These estimates verify that ignoring the welfare effects of housing price adjustments and changes in expenditures on public assistance programs results in much larger estimates of mobility costs for both high-skill and low-skill workers. In this scenario, the mobility cost estimates for low-skill workers are significantly larger in magnitude ($\sigma^L = -0.201$ versus $\sigma^H = -0.107$). Also, the difference between these coefficients is highly significant ($p < 0.001$). To compare to the baseline estimates, the mobility costs are roughly three times larger for low-skill workers and two times larger for high-skill workers when ignoring housing costs and transfer payments.[44]

The third and fourth rows report model estimates when only housing and only transfers are "shut down", respectively. The estimated mobility cost functions from these rows and the first

[43] Wages did not respond asymmetrically but population and employment did, which suggests constant returns to scale. If there were decreasing returns to scale, then the asymmetric response of employment to the local labor demand shock would imply an asymmetric wage response, as well.

[44] The estimated mobility cost functions are also statistically significantly convex, implying that the mobility cost of the marginal out-migrant rises faster than the marginal in-migrant, although the magnitude of the convexity is not large.

two rows are graphed in Figure 6. Both the figure and the model estimates (see column (9)) suggest that transfer payments are responsible for a majority of the relative difference in mobility by skill. However, the magnitudes of mobility cost estimates are much larger for both types of workers when housing expenditures are ignored. In other words, the asymmetric population response for both high-skill and low-skill workers is primarily due to the asymmetric housing supply curve, while the differential response by skill is primarily due to transfer payments.

The fifth row assumes the demand for housing is homothetic so that the housing expenditure shares are the same across the two skill groups. I choose $s^L_{\mathcal{H}} = s^H_{\mathcal{H}} = 0.33$ to match the average housing expenditure share across the entire population. The results are fairly similar to the baseline results in the first row, implying that the non-homotheticity assumed in the baseline model does not substantially account for the differential out-migration rates by skill.

Rows 6 and 7 in Table 7 report estimates which impose alternative values of $\sigma_{H,L}$. First, I impose $\sigma_{H,L} = 20$, which corresponds to the two types of labor being close to perfect substitutes, and the results are fairly similar. The next row imposes $\sigma_{H,L} = 0.1$, which corresponds to the two types being close to perfect complements, and the housing supply curve estimates are much noisier. Interestingly, the fit of the model is best when using $\sigma_{H,L} = 1.4$ (row 1) following Katz and Murphy (1992), as opposed using either of the two extreme values of $\sigma_{H,L}$.

The next row of Table 7 (row 8) uses an alternative measure of wages. As discussed above, the preferred measure of wages ("adjusted wages") assumes that most of the observed change in labor force participation is involuntary. This measure was chosen to provide an upper bound of estimated mobility costs. As an alternative, row 7 reports results using the "residualized wage" measure (see Section 4 for definition). Since residualized wages do not account for changes in labor force participation, the estimated mobility cost parameters are much lower. In fact, using this alternative wage measure, I cannot reject the null hypothesis that mobility costs are zero for low-skill workers. Overall, I conclude that these results suggest that mobility costs for both high-skill and low-skill workers are at most modest. Even under the extreme assumption that reservation wages are negligible, the estimated mobility costs are still much lower than would be implied by focusing solely on wages.[45]

[45] The final row reports estimates which drop the labor demand curve moments. The reason why alternative assumptions on the elasticity of substitution did not substantially affect the estimated mobility cost functions is

One use of the GMM estimates is to construct out-of-sample counterfactual simulations of alternative policies regarding social transfers. Figure 7 reports results from one such simulation. In this simulation, the system of means-tested transfers (summarized by the parameter Ψ) has been replaced by a system of mobility subsidies which reduces the mobility costs of all workers by 50%.[46] Each panel in the figure shows the response of a different endogenous variable. The figure shows that the mobility subsidies increase magnitude of low-skill out-migration following adverse shocks relative to the system of means-tested transfer payments. Therefore, the high-skill population share is much less responsive to shifts in local labor demand with mobility subsidies. One motivation for such a policy would be if there exist strong negative externalities from increasing the concentration of low-skill workers in a particular area; in this case, mobility subsidies appear to provide wage insurance to low-skill workers without differentially reducing their incentive to out-migrate.

7 Conclusion

Low-skill workers are comparatively immobile. When labor demand slumps in a city, college-educated workers tend to relocate whereas non-college workers are disproportionately likely to remain to face declining wages and employment. These facts may indicate that mobility is disproportionately costly for low-skill workers. This paper proposes and tests an alternative explanation, which is that the incidence of adverse labor demand shocks is borne in large part by (falling) real estate rental prices and (rising) social transfers. The spatial equilibrium model developed in this paper illustrates how wages, employment, population, housing prices, and transfer payments re-equilibrate after a local labor demand shock. Appropriately parameterized, this model identifies both the magnitude of unobserved mobility costs by skill and the shape of the local housing supply curve.

Using U.S. Census data, nonlinear reduced form estimates of the effect of plausibly exogenous

that the labor demand moments contribute to identification only indirectly through the optimal GMM weighting matrix estimated in the first step of the two-step procedure. Therefore, it is not surprising that dropping the labor demand moments entirely does not significantly affect the estimates of the mobility cost functions (Table 7, row 8).

[46] Although this is an obviously stylized form of mobility subsidies, it is not an unrealistic approximation if the policy took the form of a tax credit that was indexed to income. Recall that mobility costs in the model are defined as a fraction of annual income.

labor demand shocks document that positive labor demand shocks increase population more than negative shocks reduce population, that this asymmetry is larger for low-skill workers, and that such an asymmetry is absent for wages, housing values, and rental prices.

These facts are consistent with the presence of limited mobility costs for high-skill and low-skill workers and a concave housing supply curve (most likely due to a durable housing stock). Estimates of a full spatial equilibrium model using a nonlinear, simultaneous equations GMM estimator are consistent with the reduced form evidence and suggest that the primary explanation for the comparative immobility of low-skilled workers is not higher mobility costs per se, but rather a lower incidence of adverse local demand shocks.

The finding that mobility costs are limited for both high-skill and low-skill workers is a necessary condition to be able to properly interpret changes in housing values due to changes in observed local amenities as a valid marginal willingness to pay for the amenity (see, for example, Chay and Greenstone (2003)). The results in this paper suggest that the assumption of perfect mobility may be a valid approximation in some of these hedonic studies, especially when evaluating changes in local amenities over decadal time horizons. It is worth stressing, however, that even over decadal time horizons the assumption of perfect mobility is only an approximation. The preferred GMM estimates in this paper imply non-negligible magnitudes of mobility costs for both high-skill and low-skill workers following large negative shocks, suggesting that it may be appropriate to also consider hedonic models which explicitly incorporate barriers to migration when the underlying changes in local amenities are large, as in Bayer et al. (2008).

One important area of future work is how the incidence of local labor market shocks is shared between homeowners and renters. On the one hand, homeowners' "user cost" of housing has declined following a negative labor demand shock; on the other hand, however, declines in housing values have a negative wealth effect which may affect how responsive the household is to local labor demand shocks. A full assessment of the incidence of local labor market shocks thus awaits further study. Another important area of future work is looking at individual transfer programs. For example, the federal disability insurance program rules suggest that the take-up decision is generally a once-and-for-all choice, so that disability insurance receipt is an absorbing state (Autor and Duggan, 2003). The econometric setup in this paper could be used to test whether positive shifts in local labor demand decrease DI takeup by less than negative shifts increase DI takeup.

Lastly, the finding that mobility costs are limited suggests that transfer payments may be significantly crowding out the individual migration decision for low-skill workers, which is consistent with the results in the recent "welfare magnetism" literature (see, for example, Gelbach (2004)). This implies that the social efficiency of public insurance programs may depend on the geographic breadth of an adverse labor demand shock, since when a shock is geographically broad (as during a recession), the gains to relocation are small and there is less scope for transfer payments to crowd out migration.

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Table 1
Summary Statistics

	N	Mean	Standard Dev.	Percentiles 5th	25th	50th	75th	95th
U.S. Census Data (IPUMS)								
Adult population (in millions)	645	0.425	0.856	0.060	0.093	0.177	0.392	1.477
Employment (in millions)	645	0.303	0.596	0.041	0.067	0.127	0.283	1.036
Employment-to-population ratio	645	0.711	0.051	0.625	0.680	0.714	0.748	0.786
Income per adult (in $000s)	645	14.979	3.167	10.516	12.871	14.664	16.674	20.079
Residualized wage ($)	645	11.545	1.207	9.801	10.718	11.399	12.304	13.712
Residualized wage, LFP adjusted ($)	645	8.225	1.131	6.593	7.496	8.142	8.911	10.095
College share of adult population	645	0.190	0.063	0.105	0.143	0.181	0.226	0.305
College share of employment	645	0.221	0.065	0.131	0.173	0.213	0.257	0.341
Average housing value (in $000s)	645	97.449	45.450	58.005	71.527	84.774	107.212	196.809
Average gross rent (in $000s)	645	5.229	1.014	4.055	4.579	5.017	5.581	7.196
REIS Data								
Food stamps + Income maintenance (in $000s per non-college adult)	645	0.652	0.325	0.247	0.429	0.594	0.792	1.286

Notes: Baseline sample is a balanced panel of 215 Metropolitan Statistical Areas (MSAs), and all observations are MSA-year. IPUMS data are the 1980, 1990, and 2000. The REIS data are county-level and annual, but are aggregated to MSAs using the 1990 MSA definitions. All dollar values in this table are nominal, but all dollar-valued variables are converted to real dollars in the analysis. All specifications in subsequent tables are in first differences, so the three decades in this data set become two 10-year changes (thus, N = 430 in the regressions that follow).

Table 2
The Effects of Local Labor Demand Shocks

Dependent Variable:	(1) Population	(2) Employment	(3) Emp-to-Pop Ratio	(4) Income per 18-64 Adult	(5) Residualized Average Local Wage	(6) Residualized Wage, LFP Adjusted ("Adjusted Wage")
% Change in predicted employment **(β)**	1.802	2.056	0.089	0.959	0.353	0.520
	(0.445)	(0.465)	(0.038)	(0.137)	(0.086)	(0.109)
	[0.000]	[0.000]	[0.019]	[0.000]	[0.000]	[0.000]
(% Change in predicted employment)^2 **(δ)**	28.010	32.537	1.210	0.382	-0.756	1.458
	(7.905)	(9.101)	(0.797)	(2.859)	(1.643)	(2.426)
	[0.000]	[0.000]	[0.130]	[0.894]	[0.646]	[0.549]
Marginal effect at $-\sigma$ **(A)**	-0.152	-0.214	0.005	0.932	0.405	0.419
(i.e., $\beta - 2\delta\sigma$)	(0.847)	(0.898)	(0.055)	(0.205)	(0.156)	(0.174)
	[0.858]	[0.812]	[0.930]	[0.000]	[0.010]	[0.017]
Marginal effect at $+\sigma$ **(B)**	3.757	4.327	0.174	0.985	0.300	0.622
(i.e., $\beta + 2\delta\sigma$)	(0.535)	(0.658)	(0.077)	(0.274)	(0.130)	(0.225)
	[0.000]	[0.000]	[0.026]	[0.000]	[0.022]	[0.006]
p-value of test **(A)** = **(B)**	0.000	0.000	0.130	0.894	0.646	0.549
p-value of nonparametric specification test	0.000	0.000	0.259	0.492	0.628	0.451
R^2	0.315	0.354	0.605	0.670	0.471	0.340
N	430	430	430	430	430	430

<u>Notes:</u> All columns report OLS results from estimating equation (7). Data come from IPUMS 1980, 1990, and 2000 census extracts. Final sample is a balanced panel of 215 MSAs. Dependent variable is always the percentage change across periods, except for column (3) where it is the percentage point change. The Residualized Wage in column (5) controls for observed compositional changes in the labor force between periods. The Adjusted Wage in column (6) uses the Residualized Wage and additionally accounts for changes in labor force participation. The % Change in predicted employment is formed by interacting cross-sectional differences in industrial composition with national changes in industry employment shares. The nonparametric specification test tests the null hypothesis that a linear model is appropriate against a nonparametric alternative. See main text and Data Appendix for more details. All specifications include year fixed effects. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each metropolitan area over time, are in parenthesis and p-values are in brackets.

Table 3
Effects of Labor Demand Shocks by Skill

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Adult Population		Total Employed		College Share of …		Residualized Wage		Adjusted Wage	
Dependent Variable:	College	Non-College	College	Non-College	… Adult Population	… Total Employed	College	Non-College	College	Non-College
% Change in predicted empl. (***β***)	1.925	1.609	2.196	1.860	0.051	0.039	0.296	0.346	0.467	0.514
	(0.544)	(0.436)	(0.553)	(0.457)	(0.024)	(0.027)	(0.080)	(0.085)	(0.100)	(0.107)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.036]	[0.151]	[0.000]	[0.000]	[0.000]	[0.000]
(% Change in predicted empl.)^2 (***δ***)	35.204	28.057	36.980	32.896	-0.816	-1.022	-1.322	-0.829	-0.498	1.525
	(10.363)	(7.692)	(10.993)	(8.834)	(0.349)	(0.376)	(1.399)	(1.628)	(2.011)	(2.372)
	[0.001]	[0.000]	[0.001]	[0.000]	[0.020]	[0.007]	[0.346]	[0.611]	[0.805]	[0.521]
Marginal effect at $-\sigma$ **(A)**	-0.531	-0.349	-0.384	-0.436	0.108	0.110	0.389	0.404	0.502	0.408
	(0.989)	(0.844)	(0.999)	(0.892)	(0.033)	(0.038)	(0.140)	(0.153)	(0.168)	(0.169)
	[0.592]	[0.679]	[0.701]	[0.625]	[0.001]	[0.004]	[0.006]	[0.009]	[0.003]	[0.017]
Marginal effect at $+\sigma$ **(B)**	4.382	3.566	4.777	4.155	-0.006	-0.032	0.204	0.288	0.432	0.621
	(0.812)	(0.494)	(0.889)	(0.619)	(0.035)	(0.038)	(0.110)	(0.129)	(0.176)	(0.222)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.862]	[0.397]	[0.066]	[0.027]	[0.015]	[0.006]
p-value of test **(A)** = **(B)**	0.001	0.000	0.001	0.000	0.020	0.007	0.346	0.611	0.805	0.521
p-value of nonparam. specification test	0.000	0.000	0.000	0.000	0.134	0.073	0.621	0.612	0.605	0.428
R^2	0.558	0.240	0.569	0.262	0.772	0.751	0.432	0.659	0.472	0.210
N	430	430	430	430	430	430	430	430	430	430

Notes: All columns report OLS results from estimating equation (7). Data come from IPUMS 1980, 1990, and 2000 census extracts. Final sample is a balanced panel of 215 MSAs. Dependent variable is always the percentage change across periods, except in columns (5) and (6) which report percentage point changes in the college share. The % Change in predicted employment is formed by interacting cross-sectional differences in industrial composition with national changes in industry employment shares. See Table 2, main text, and Data Appendix for more details. All specifications include year fixed effects. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each metropolitan area over time, are in parenthesis and p-values are in brackets.

Table 4
Effects of Labor Demand Shocks on Housing Market
and Public Assistance Expenditures

Dependent Variable:	(1) Residualized Rental Prices	(2) Residualized Housing Values	(3) Food Stamps + Income Maintenance Expenditures
% Change in predicted employment **(β)**	0.842	0.714	-2.367
	(0.151)	(0.360)	(0.615)
	[0.000]	[0.048]	[0.000]
(% Change in predicted employment)^2 **(δ)**	-0.999	-2.765	-21.779
	(2.758)	(6.310)	(12.139)
	[0.717]	[0.662]	[0.074]
Marginal effect at $-\sigma$ **(A)**	0.912	0.907	-0.847
	(0.243)	(0.580)	(1.030)
	[0.000]	[0.119]	[0.412]
Marginal effect at $+\sigma$ **(B)**	0.773	0.521	-3.887
	(0.247)	(0.558)	(1.064)
	[0.002]	[0.351]	[0.000]
p-value of test **(A)** = **(B)**	0.717	0.662	0.074
p-value of nonparametric specification test	0.596	0.295	0.241
R^2	0.099	0.144	0.403
N	430	430	430

Notes: All columns report OLS results from estimating equation (7). Data come from IPUMS 1980, 1990, and 2000 census extracts and the REIS database. The REIS database contains total county-level expenditures on Food Stamps and Income Maintenance programs. These data are aggregated to MSAs using 1990 MSA definition and adjusted per non-college capita using MSA population estimates from the Census. Final sample is a balanced panel of 215 MSAs. Dependent variable is always the percentage change across periods. The % Change in predicted employment is formed by interacting cross-sectional differences in industrial composition with national changes in industry employment shares. See Table 2, main text, and Data Appendix for more details. All specifications include year fixed effects. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each metropolitan area over time, are in parenthesis and p-values are in brackets.

Table 5
Effects of Alternative Measures of Labor Demand Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	Industries Used to Construct Change in Predicted Employment					
	All Industries	Drop Trending	Drop Volatile	Drop Stable	Drop Other	Drop Catch-All
Panel A: Dependent Variable is % Change in Population						
% Change in predicted employment (β)	1.802	3.768	2.170	1.855	1.692	2.196
	(0.445)	(0.667)	(0.538)	(0.455)	(0.578)	(0.545)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]	[0.000]
(% Change in predicted employment)^2 (δ)	28.010	30.589	35.251	30.662	45.861	43.311
	(7.905)	(10.665)	(13.351)	(8.727)	(12.455)	(13.348)
	[0.000]	[0.005]	[0.009]	[0.001]	[0.000]	[0.001]
p-value of nonparametric specification test	0.000	0.012	0.002	0.013	0.000	0.000
Panel B: Dependent Variable is % Change in Adjusted Wage						
% Change in predicted employment (β)	0.520	1.180	0.388	0.532	0.478	0.687
	(0.109)	(0.208)	(0.131)	(0.102)	(0.134)	(0.126)
	[0.000]	[0.000]	[0.003]	[0.000]	[0.000]	[0.000]
(% Change in predicted employment)^2 (δ)	1.458	2.543	-0.689	1.909	3.325	0.944
	(2.426)	(4.083)	(2.766)	(2.274)	(3.425)	(2.674)
	[0.549]	[0.534]	[0.803]	[0.402]	[0.333]	[0.724]
p-value of nonparametric specification test	0.451	0.378	0.069	0.211	0.100	0.193
Panel C: Dependent Variable is % Change in Rental Prices						
% Change in predicted employment (β)	0.842	1.328	0.812	0.908	0.727	0.994
	(0.151)	(0.303)	(0.173)	(0.152)	(0.176)	(0.190)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
(% Change in predicted employment)^2 (δ)	-0.999	-6.889	-2.104	0.563	1.012	-4.079
	(2.758)	(5.521)	(3.787)	(2.964)	(3.655)	(3.779)
	[0.717]	[0.213]	[0.579]	[0.850]	[0.782]	[0.282]
p-value of nonparametric specification test	0.596	0.437	0.392	0.556	0.063	0.490

Notes: N = 430. All columns report OLS results from estimating equation (7). Data come from IPUMS 1980, 1990, and 2000 census extracts. Final sample is a balanced panel of 215 MSAs. Dependent variable is always the percentage change across periods. The % Change in predicted employment is formed by interacting cross-sectional differences in industrial composition with national changes in industry employment shares. Column (1) reproduces the baseline specification; remaining columns construct predicted employment changes by excluding alternative sets of industries. See Table 2, main text, Appendix Table A1, and Data Appendix for more details. All specifications include year fixed effects. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each metropolitan area over time, are in parenthesis and p-values are in brackets.

Table 6
Alternative Sample Definitions and Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Dependent Variable is % Change in Population								
% Change in predicted employment (***β***)	1.802	1.351	1.821	2.517	1.342	1.368	1.419	0.509
	(0.445)	(0.309)	(0.414)	(0.511)	(0.547)	(0.947)	(0.674)	(0.360)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.015]	[0.150]	[0.036]	[0.158]
(% Change in predicted employment)^2 (***δ***)	28.010	18.110	24.051	30.163	25.102	32.652	38.327	17.196
	(7.905)	(3.823)	(7.528)	(6.297)	(7.842)	(20.344)	(22.388)	(6.200)
	[0.000]	[0.000]	[0.002]	[0.000]	[0.002]	[0.110]	[0.088]	[0.006]
p-value of nonparametric specification test	0.000	0.001	0.000	0.002	0.007	0.007	0.015	0.003
Panel B: Dependent Variable is % Change in Adjusted Wage								
% Change in predicted employment (***β***)	0.520	1.224	0.432	0.242	0.590	0.896	0.423	0.418
	(0.109)	(0.542)	(0.096)	(0.101)	(0.102)	(0.245)	(0.115)	(0.091)
	[0.000]	[0.025]	[0.000]	[0.017]	[0.000]	[0.000]	[0.000]	[0.000]
(% Change in predicted employment)^2 (***δ***)	1.458	8.948	0.925	0.745	0.246	3.840	3.885	2.129
	(2.426)	(6.080)	(2.229)	(1.240)	(2.256)	(4.521)	(3.259)	(1.316)
	[0.549]	[0.143]	[0.678]	[0.548]	[0.913]	[0.397]	[0.235]	[0.107]
p-value of nonparametric specification test	0.451	0.475	0.299	0.217	0.584	0.153	0.293	0.363
Panel C: Dependent Variable is % Change in Rental Prices								
% Change in predicted employment (***β***)	0.842	0.663	0.804	0.791	0.728	0.934	0.821	0.814
	(0.151)	(0.367)	(0.135)	(0.134)	(0.145)	(0.364)	(0.173)	(0.126)
	[0.000]	[0.073]	[0.000]	[0.000]	[0.000]	[0.011]	[0.000]	[0.000]
(% Change in predicted employment)^2 (***δ***)	-0.999	-4.675	0.178	-3.422	-2.087	4.120	3.698	1.512
	(2.758)	(5.530)	(2.645)	(1.652)	(2.546)	(5.974)	(5.080)	(1.948)
	[0.717]	[0.399]	[0.946]	[0.040]	[0.413]	[0.491]	[0.467]	[0.438]
p-value of nonparametric specification test	0.596	0.162	0.412	0.136	0.591	0.240	0.317	0.184
Alternative Samples and Alternative Specifications								
Baseline sample (N = 430)	X				X	X	X	X
Add 2000-2007 change (N = 586)		X						
Add in non-MSA regions of states (N = 528)			X					
Long differences (N = 215)				X				
Region-specific linear time trends					X			
MSA-specific linear time trends						X		
Drop outlying 5% shocks							X	
Predicted employment from CBP								X

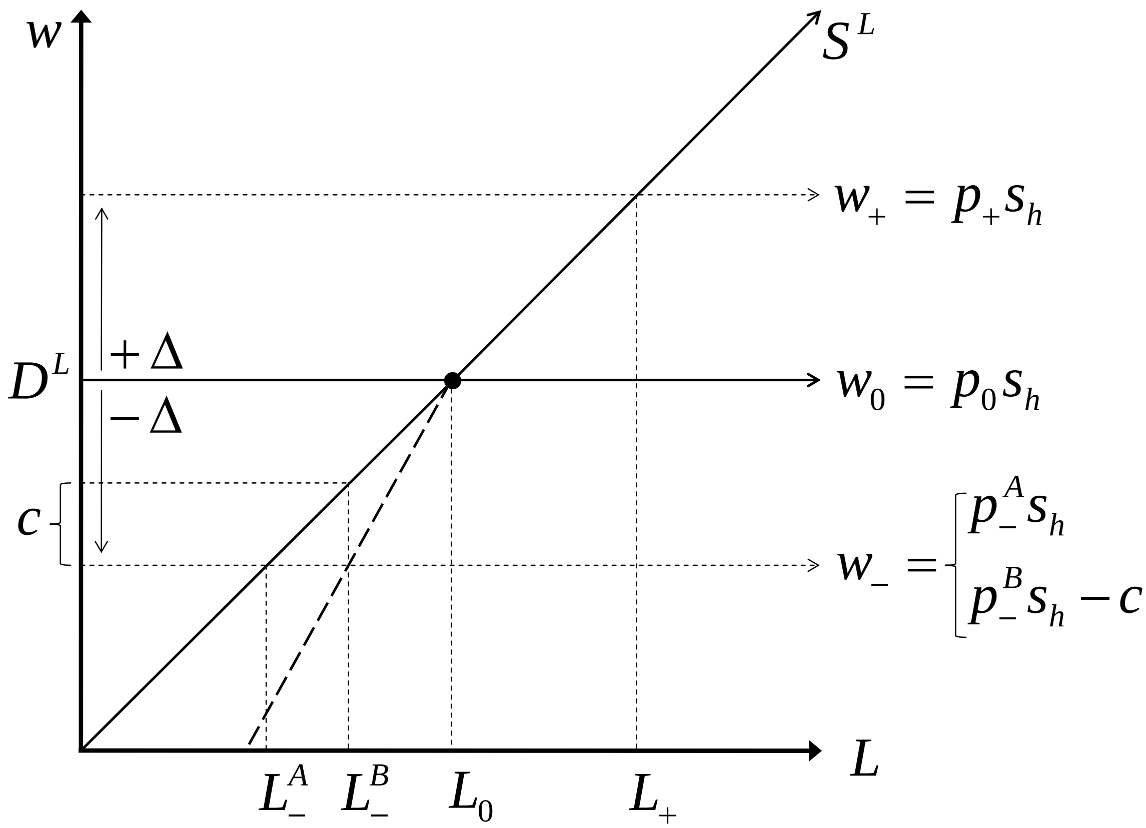
Notes: All columns report OLS results from estimating equation (7). Data come from IPUMS 1980, 1990, and 2000 census extracts. Final sample is a balanced panel of 215 MSAs. Dependent variable is always the percentage change across periods. The % Change in predicted employment is formed by interacting cross-sectional differences in industrial composition with national changes in industry employment shares. Column (1) reproduces the baseline specification; remaining columns construct predicted employment changes using subsets of industries. See Table 2, main text, and Data Appendix for more details. All specifications include year fixed effects. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each metropolitan area over time, are in parenthesis and p-values are in brackets.

Table 7
GMM Estimates of Full Model

Row	Model	(1) Housing Supply Curve σ^h	(2) Housing Supply Curve β^h	(3) High-Skill Mobility Cost Function σ^H	(4) High-Skill Mobility Cost Function β^H	(5) Low-Skill Mobility Cost Function σ^L	(6) Low-Skill Mobility Cost Function β^L	(7) Transfer Payment Elasticity ψ	(8) Returns to Scale α	(9) H$_0$: $\sigma^L = \sigma^H$ $\sigma^L - \sigma^H$	(10) χ^2 test statistic
(1)	Baseline Model	1.201	6.306	-0.066	-1.044	-0.065	-0.861	-3.838	1.038	-0.001	21.088
		(0.407)	(1.774)	(0.016)	(0.766)	(0.019)	(0.738)	(0.447)	(0.025)	(0.015)	[0.515]
		[0.003]	[0.000]	[0.000]	[0.174]	[0.001]	[0.244]	[0.000]	[0.129]	[0.951]	
(2)	No Housing; No Transfers	1.009	6.472	-0.107	-0.495	-0.201	-0.900	-4.341	1.020	0.093	25.262
		(0.432)	(2.685)	(0.017)	(0.408)	(0.024)	(0.276)	(0.577)	(0.021)	(0.016)	[0.285]
		[0.020]	[0.016]	[0.000]	[0.226]	[0.000]	[0.001]	[0.000]	[0.336]	[0.000]	
(3)	No Transfers	0.872	5.604	-0.060	-1.060	-0.119	-0.938	-4.256	1.030	0.059	18.881
		(0.399)	(2.517)	(0.016)	(0.839)	(0.022)	(0.484)	(0.572)	(0.023)	(0.016)	[0.653]
		[0.030]	[0.027]	[0.000]	[0.207]	[0.000]	[0.053]	[0.000]	[0.192]	[0.000]	
(4)	No Housing	1.060	6.436	-0.106	-0.504	-0.135	-0.775	-4.225	1.020	0.029	25.593
		(0.413)	(2.478)	(0.015)	(0.410)	(0.019)	(0.286)	(0.509)	(0.020)	(0.014)	[0.270]
		[0.011]	[0.010]	[0.000]	[0.220]	[0.000]	[0.007]	[0.000]	[0.316]	[0.042]	
(5)	$s_H = s_L = 0.33$	1.151	6.318	-0.059	-1.141	-0.067	-1.005	-3.889	1.035	0.007	20.406
		(0.413)	(1.875)	(0.016)	(0.875)	(0.019)	(0.739)	(0.450)	(0.024)	(0.015)	[0.558]
		[0.006]	[0.001]	[0.000]	[0.193]	[0.000]	[0.174]	[0.000]	[0.145]	[0.611]	
(6)	$\sigma_{H,L} = 20$	2.019	5.844	-0.033	0.847	-0.038	0.495	-3.626	0.994	0.005	25.320
		(0.654)	(1.539)	(0.013)	(0.443)	(0.015)	(0.541)	(0.455)	(0.030)	(0.005)	[0.282]
		[0.002]	[0.000]	[0.015]	[0.057]	[0.016]	[0.361]	[0.000]	[0.849]	[0.360]	
(7)	$\sigma_{H,L} = 0.1$	0.601	10.748	-0.065	-1.954	-0.066	-1.334	-3.695	1.236	0.001	38.345
		(0.221)	(2.128)	(0.013)	(0.810)	(0.016)	(0.667)	(0.410)	(0.020)	(0.014)	[0.017]
		[0.007]	[0.000]	[0.000]	[0.016]	[0.000]	[0.046]	[0.000]	[0.000]	[0.939]	
(8)	Alternative Wage Measure	0.662	8.611	-0.032	-3.011	-0.007	-10.391	-3.315	1.062	-0.025	26.389
	(Residualized Wages)	(0.363)	(2.806)	(0.010)	(1.304)	(0.006)	(2.715)	(0.497)	(0.011)	(0.011)	[0.235]
		[0.069]	[0.002]	[0.003]	[0.021]	[0.286]	[0.000]	[0.000]	[0.000]	[0.026]	
(9)	Drop Labor Demand Moments	1.209	5.305	-0.085	-0.604	-0.079	-0.089	-4.270		-0.006	11.892
		(0.700)	(3.291)	(0.022)	(0.692)	(0.023)	(0.626)	(0.448)	*N/A*	(0.015)	[0.537]
		[0.085]	[0.108]	[0.000]	[0.383]	[0.001]	[0.887]	[0.000]		[0.677]	

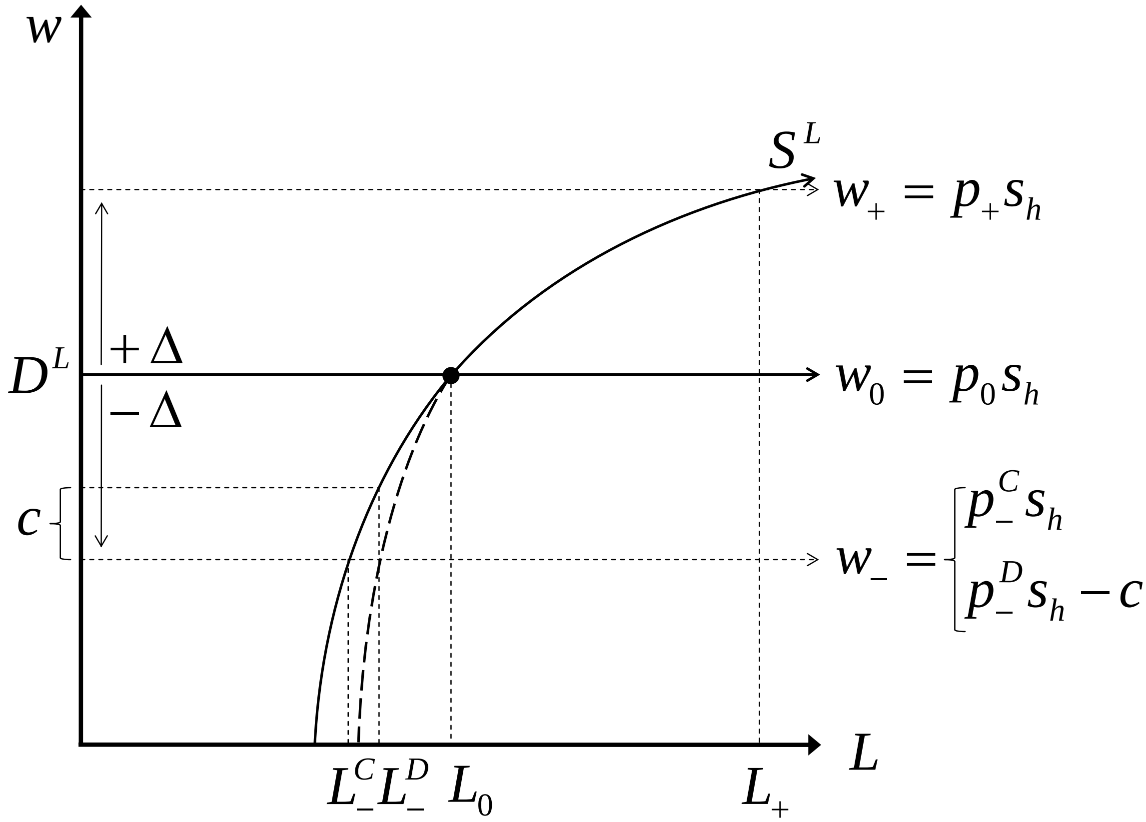
Notes: All rows report estimates of the full model using a nonlinear, simultaneous equations GMM estimator. Alternate specifications are presented in each row; parameter estimates are listed in the columns. See Section 6 of main text and Section A.5 of the Online Appendix for more details. Asymptotic standard errors are in parenthesis and p-values are in brackets. In column (8), the p-value reported is for the test of whether the point estimate is statistically significantly different from 1.

Figure 1: Constant Housing Supply Elasticity



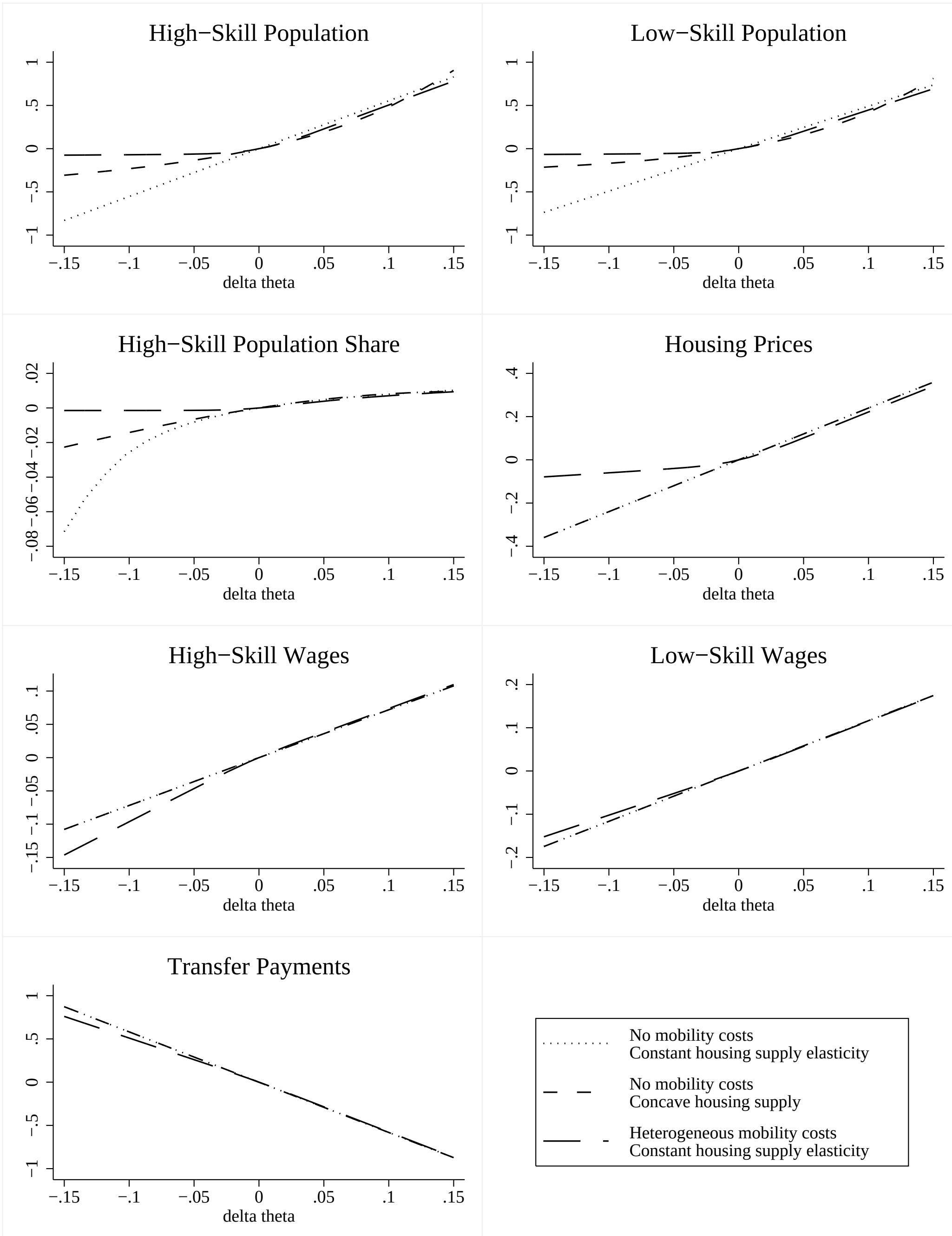
Notes: This figure displays the equilibrium response when the housing supply elasticity is constant. The initial equilibrium wages, labor supply, and housing prices are given by the dot in the center of the figure. An exogenous increase in wages encourages in-migration until labor supply rises to L_+. At this point, housing prices have risen to completely offset the increase in wages, restoring the no-arbitrage condition for workers. If there are no mobility costs, then the equilibrium response of an equal-sized exogenous decrease in wages is *symmetric*, as shown by L_-^A. If out-migration is costly, however, then following a negative shock, the marginal out-migrant must be indifferent between staying and paying c to out-migrate. These mobility costs cause both population and housing prices to respond *asymmetrically*: positive shocks increase population and housing prices more than negative shocks reduce them.

Figure 2: Concave Housing Supply Curve



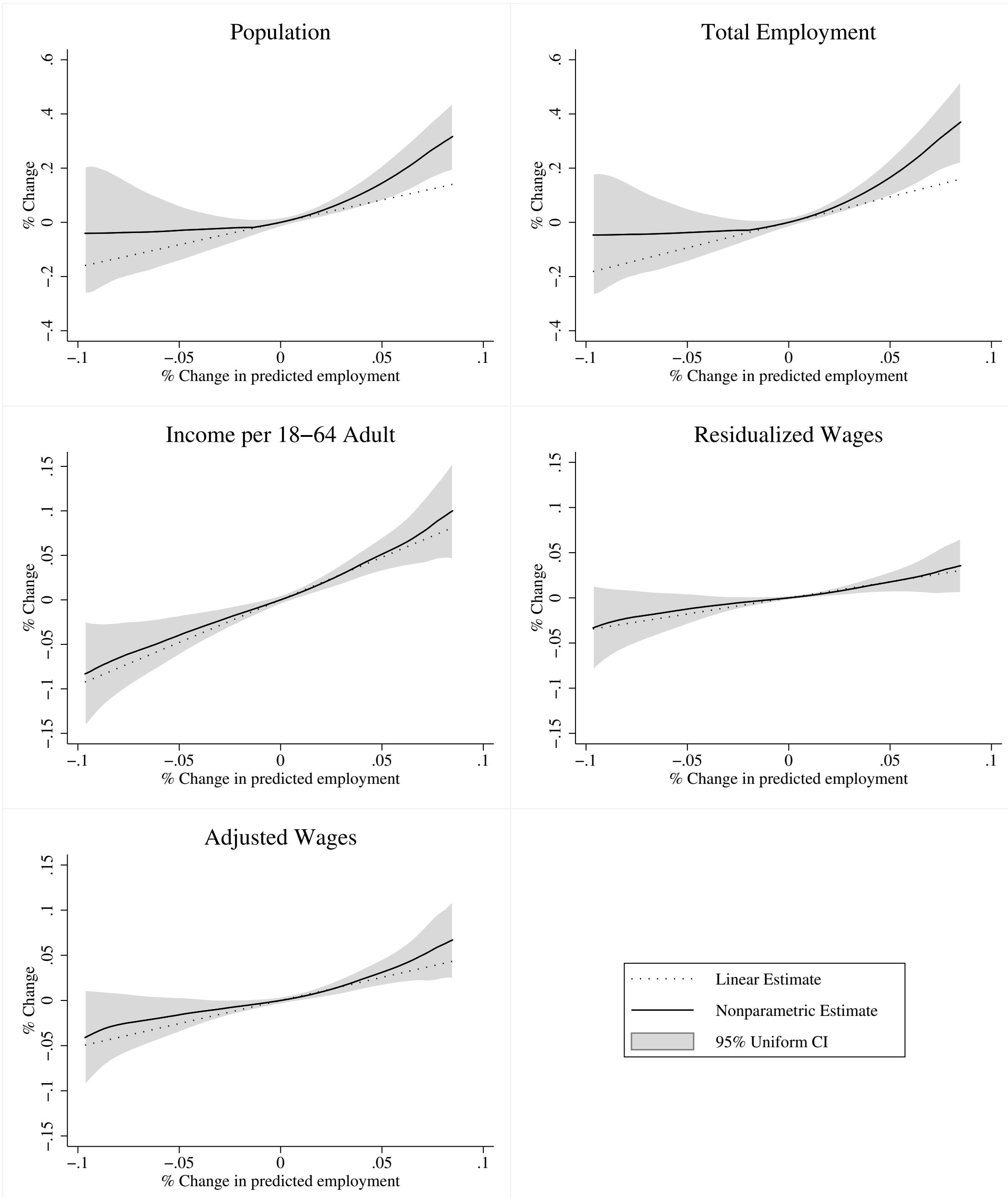
<u>Notes:</u> This figure displays the equilibrium response when the housing supply curve is concave. As the main text and Appendix describe in more detail, a concave housing supply curve is consistent with a durable housing stock that is not destroyed once created. As in figure 1, the initial equilibrium wages, labor supply, and housing prices are given by the dot in the center of the figure. An exogenous increase in wages encourages in-migration until labor supply rises to L_+. At this point, housing prices have risen to completely offset the increase in wages, restoring the no-arbitrage condition for workers. If there are no mobility costs, then housing prices still respond symmetrically (p_-^C). Intuitively, housing costs still must adjust to exactly offset the wage changes. Only population responds asymmetrically (as shown by L_-^C). If workers have mobility costs, then the asymmetry of the population response is even greater (see L_-^D), and in this case housing prices also respond asymmetrically.

Figure 3: Model Simulations



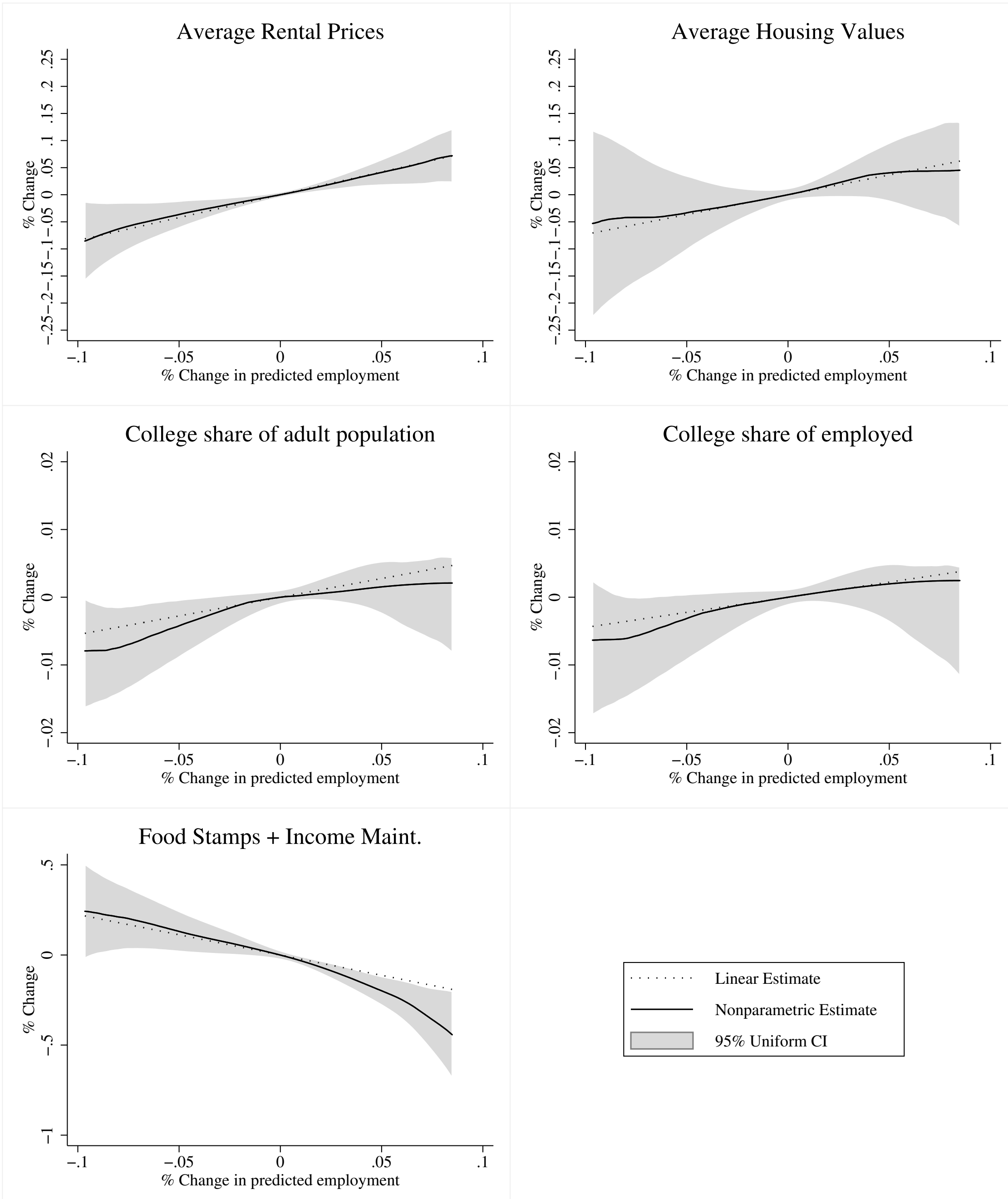
Notes: This figure displays simulated data from the model described in Section 2. See the Appendix for more details on the simulation. The graphs clarify that an asymmetric response of population to the labor demand shock (delta theta) indicates the existence of a concave housing supply curve and/or the existence of heterogeneous mobility costs. The response of housing prices isolates the importance of mobility costs.

Figure 4: Reduced Form Results



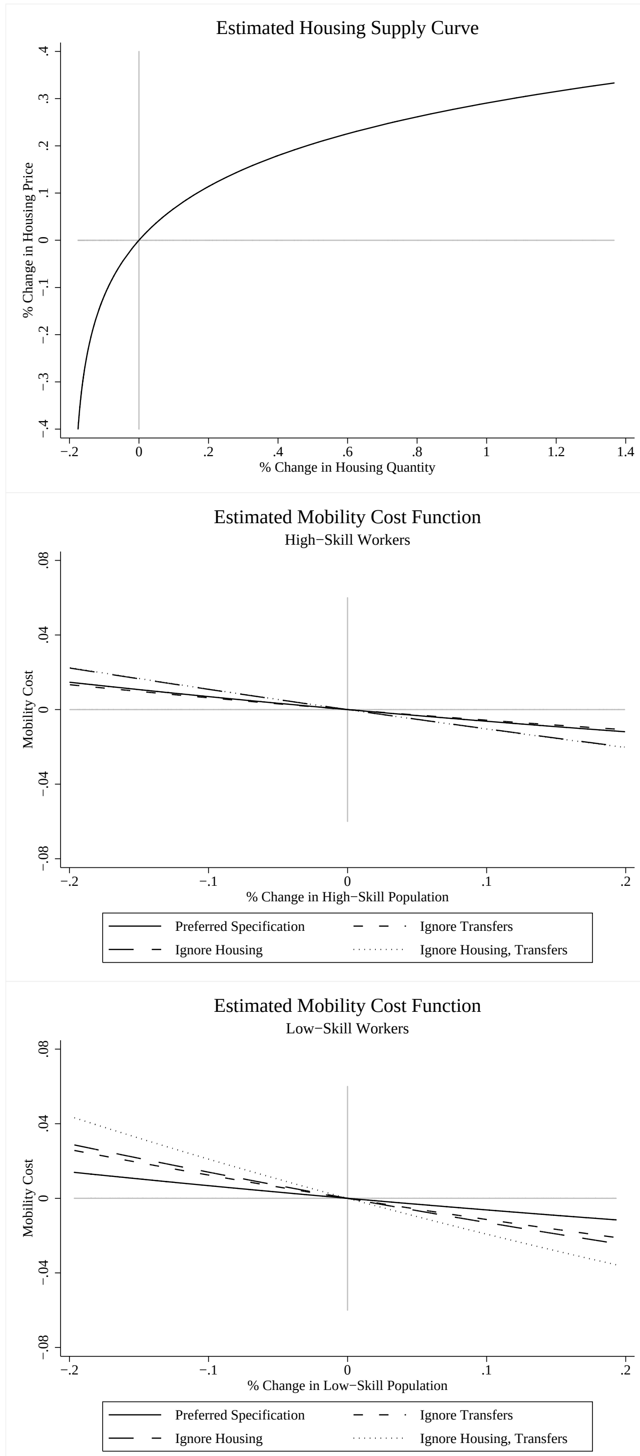
Notes: This figure reports nonparametric reduced form estimates using U.S. Census data and REIS data. See Appendix for details on the data set. All graphs are nonparamaetric local linear regressions. All results include year fixed effects in the nonparametric model. The estimates are constrained to be monotonic following the rearrangement procedure of Chernozhukov, Fernandez-Val, and Galichon (2003). The 95 percent uniform confidence intervals are computed using 10,000 bootstrap replications, resampling MSAs with replacement. In each bootstrap step, an undersmoothed local linear bandwidth is chosen following Hall (1992).

Figure 5: Reduced Form Results, Continued



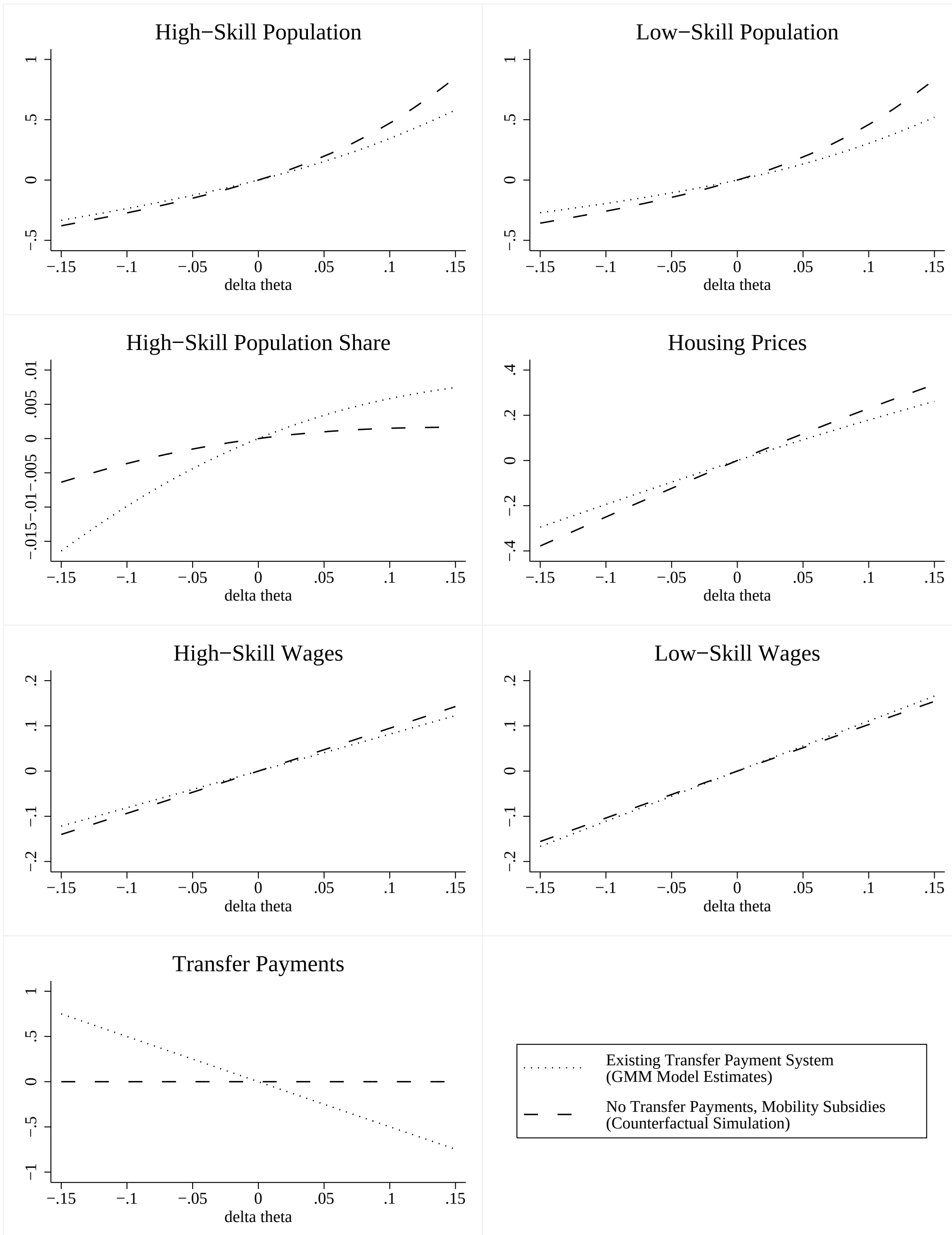
Notes: This figure reports nonparametric reduced form estimates using U.S. Census data and REIS data. See Appendix for details on the data set. All graphs are nonparamaetric local linear regressions. All results include year fixed effects in the nonparametric model. The estimates are constrained to be monotonic following the rearrangement procedure of Chernozhukov, Fernandez-Val, and Galichon (2003). The 95 percent uniform confidence intervals are computed using 10,000 bootstrap replications, resampling MSAs with replacement. In each bootstrap step, an undersmoothed local linear bandwidth is chosen following Hall (1992).

Figure 6: GMM Estimates



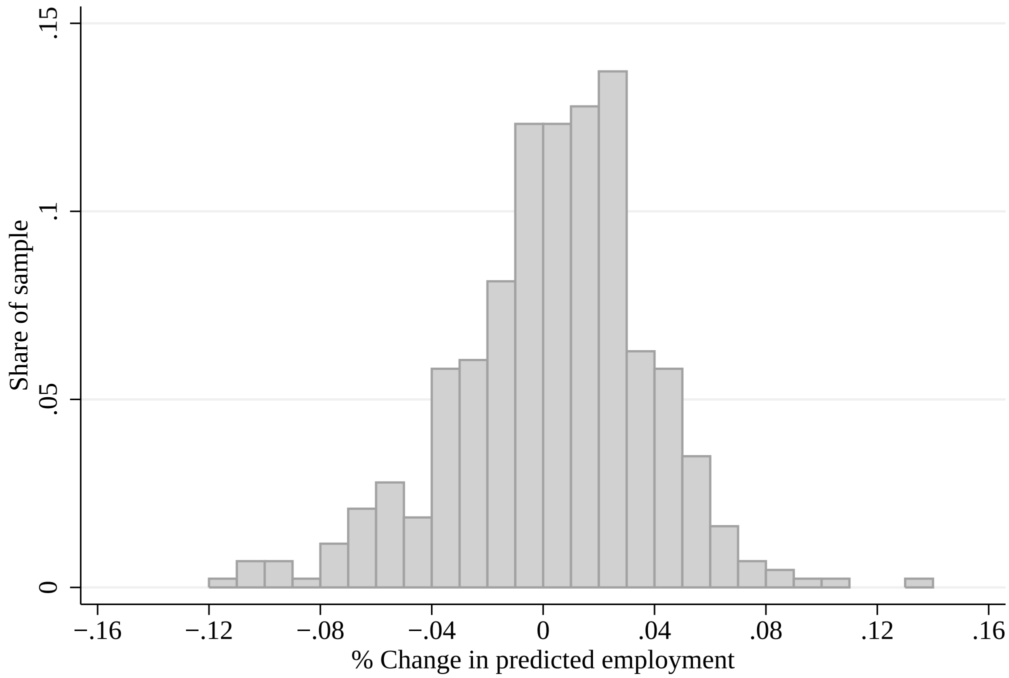
Notes: This figure reports GMM estimates of the full model. The top figure presents the housing supply curve that is estimated in the baseline model (Table 7, row 1). The middle and bottom figures report estimated mobility functions under various assumptions about housing expenditure shares and transfer payments. See Section 6 and the Appendix for more details on the GMM estimation.

Figure 7: Counterfactual Simulation



Notes: This figure reports simulations based on GMM estimates of the full model. The GMM estimates are used to run simulations similar to those presented in Figure 3. The graphs report results of two simulations: (1) simulation based on estimates of the baseline GMM model using the existing transfer payment system and (2) counterfactual simulation based on same estimates but transfer payment system is replaced with mobility subsidies which reduce mobility costs by 50%.

Appendix Figure A1: Symmetry of Predicted Employment Shock



Notes: This figure displays a histogram of the local labor demand shock used throughout the paper. The symmetry of the distribution of the shock implies that the estimated asymmetric responses are not due (in part) to underlying asymmetries in the shock itself.