Labor Market Power and Spatial Policies

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November 20, 2025

Abstract

Spatial models often assume competitive labor markets. However, place-based policies may interact with local monopsony. We build a spatial model with labor market power and estimate it using four decades of U.S. data. We estimate falling wage markdowns, driven by increased job-switching across industries and growth in the number of local firms. Raising housing supply elasticities in large productive locations increases welfare but has little impact on monopsony, producing aggregate outcomes similar to a competitive model. In contrast, migration subsidies reduce markdowns by increasing labor supply elasticities, yielding different welfare effects from the standard model without monopsony.

Keywords: Labor Market Power; Spatial Models; Housing Policies; Migration Policies.

JEL Classification: R13; R23; R28.

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We are grateful to Nick Kuminoff, Alvin Murphy, Kelly Bishop, Esteban Rossi-Hansberg, and audiences at Bank of Italy and the EPGE Applied micro workshop for helpful comments. Igor de Araujo Brito, Ricardo Jose Ramos Fontes, and Edilson Figueiredo provided excellent research assistance. This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES), Grant # 001. Luccioletti gratefully acknowledges funding from Bank of Italy's research fellowship for economists. The views expressed are those of the authors and do not necessarily reflect the position of the Bank of Italy.

1 Introduction

Labor markets differ substantially across U.S. locations. In some cities, workers face many potential employers and wages closely reflect marginal products; in others, firm concentration is higher and mobility frictions limit workers' ability to access better opportunities elsewhere. Standard quantitative spatial models typically abstract from these differences and assume perfectly competitive labor markets, largely to preserve tractability in high-dimensional environments. Yet the extent of local labor market power, and the forces that shape it, may influence how workers respond to policy interventions and how gains from spatial reallocation are distributed.

This study examines when accounting for local labor market power is important for evaluating place-based policies, and when the added computational cost of modeling the monopsony margin is justified. We develop a spatial equilibrium model in which wage markdowns arise from three sources: costly migration across locations, costly switching across industries, and imperfect competition among firms within local labor markets. Workers choose where to live and which industries to work in, trading off wages, rents, amenities, and the frictions limiting their ability to relocate or change jobs. Firms hire labor in imperfectly competitive local markets (location-industry pairs), and their labor market power depends on both market concentration and the elasticity of local labor supply. The number of firms in each location-industry-year is determined endogenously through a free-entry condition, and firm productivity adjusts with local employment levels through agglomeration economies.

We estimate the model using four decades of U.S. Census data, combined with information on housing markets, firm structure, and worker mobility. We first recover migration and industry-switching costs using a BLP procedure based on individuals' discrete choices over local labor markets (Berry, Levinsohn and Pakes 1995, Bayer, Keohane and Timmins 2009). Next, we identify local labor supply elasticities using a novel shift–share instrument that exploits labor demand variation induced by free trade agreements with Canada and Mexico (CUSFTA and NAFTA). Finally, we estimate the remaining housing and labor market parameters by inverting the model's equilibrium conditions to exactly match observed wages and housing prices.

The model performs well in terms of untargeted moments. The estimated agglomeration elasticity aligns with the mean values from the literature. Moreover, the utility parameters implied by the IV yield a median labor supply elasticity within the upper range of best-practice estimates. As a robustness exercise, we recalibrate the utility parameters to match the lower end of those estimates and find that the relative contribution of each source of monopsony power remains largely unchanged.

Using the calibrated model, we document the evolution of local labor market power since 1980. Despite declining spatial mobility, local wage markdowns have fallen substantially, roughly halving over the past four decades. Two forces drive this trend. First, workers are increasingly mobile across industries, increasing the elasticity of labor supply. Second, the number of local firms has grown, lowering labor market concentration. In counterfactual decomposition exercises, these two channels jointly account for around 70% of the decline in markdowns. By contrast, changes in migration costs, while relevant for for mobility, play only a minor quantitative role in the evolution of local labor market power.

We then use the model to evaluate a set of spatial policies, which are implemented in a fiscally neutral fashion, ensuring a balanced government budget through the adjustment of income taxes. Prohibitively high cost of living in big cities has been a policy concern for many years (Glaeser and Gyourko 2002), and policies aiming to increase housing supply elasticity like laws promoting accessory dwelling units (ADU) in tight markets have gained in popularity.[2] We find that relaxing housing supply constraints in large, productive cities generates substantial reallocation and raises welfare (0.56%), but has only muted effects on local labor market power. Labor supply elasticities respond ambiguously: lower housing prices reduce out-migration from large cities while attracting in-migration from smaller ones, producing offsetting effects on monopsony. Similar offsetting forces emerge in smaller cities, where higher out-migration raises labor supply elasticities while reduced in-migration lowers them. As a result, the aggregate consequences of this policy closely resemble those predicted by a standard competitive spatial model.

In contrast, a subsidy to migrate to large cities substantially increases labor supply elasticities in those locations and meaningfully reduces local wage markdowns. This induces wage and housing price increases that are larger in a model with monopsony than in one without, leading to welfare effects that diverge across the two frameworks. Although the magnitudes are small, welfare turns slightly negative in the model with labor market power (-0.012%) and slightly positive in the competitive model (0.015%), primarily because housing prices rise less when labor market power is absent. Thus, even for a policy with relatively modest aggregate effects, modeling the monopsony margin can change the welfare evaluation. This suggests that the standard quantitative spatial model with competitive labor markets is not well suited to analyze migration subsidies, a widely studied spatial policy.

Finally, a place-based firm entry subsidy targeted at concentrated labor markets in small locations produces relatively large reductions in markdowns at comparatively low fiscal cost. By encouraging additional firm entry and intensifying local labor market competition, it delivers roughly 60% of the markdown decline achieved under the migration subsidy, while requiring only 3.4% of the additional tax revenue needed to finance the migration subsidy.

Related Literature Quantitative spatial models have been widely used to study the sorting of workers and firms, and a growing body of work incorporates labor market power into spatial settings (Bamford 2021, Ahlfeldt, Roth and Seidel 2022, Datta 2024, Bagga 2023). These models are often computationally demanding due to their high dimensionality, especially when dynamics are involved (Caliendo, Dvorkin and Parro 2019). Adding the monopsony margin typically increases this complexity. Our results show that incorporating labor market power into spatial models is not always necessary, but becomes important when policies

[2]Recent state legislation in Arizona, Colorado, Massachusetts, Iowa, and Washington prevents local jurisdictions from blocking or constraining ADU construction through owner-occupancy mandates, parking mandates, or aesthetic requirements following the example of California.

have clear and sizable effects on labor supply elasticities or firm concentration. Housing policies, for instance, can be evaluated reasonably well in competitive frameworks, whereas the analysis of migration subsidies requires explicitly modeling monopsony to capture their full effects. These findings speak to a broader literature on spatial policies and the role of place versus people-based interventions (Kline and Moretti 2014, Giannone et al. 2023, Gaubert et al. 2025).[3]

Labor market power has received renewed interest in recent years (Manning 2021, Sokolova and Sorensen 2021, Card 2022), including work documenting its substantial variation across space (Azar, Marinescu and Steinbaum 2022, Rinz et al. 2018, Azar et al. 2020). We contribute to this literature by constructing micro-founded labor supply elasticities identified with a novel shift–share IV, and by quantifying the relative importance of the different components of monopsony power: moving costs, industry-switching costs, and local employer concentration.[4] To our knowledge, this is the first decomposition of U.S. wage markdowns over the last four decades that explicitly incorporates spatial frictions. Relatedly, Berger et al. (2024) decompose the contributions of firm granularity, search frictions, and non-wage amenities to monopsony power in a model without geography, using Norwegian data.[5]

We find that markdowns have declined over time, particularly between 1980 and 2000, a pattern that differs somewhat from Yeh, Macaluso and Hershbein (2022), who use a control-function approach and find markdowns falling between 1980 and 2000 but rising thereafter. More consistent with our results, Deb et al. (2022) find that U.S. markdowns have remained relatively stable since 2000, using a structural framework similar to Berger, Herkenhoff and Mongey (2022).

The remainder of the paper is organized as follows. Section 2 shows motivating facts. In Section 3, we describe our model framework. Section 4 presents the data and the estimation procedure. In Sections 5 and 6, we report our results and counterfactual exercises. Finally, Section 7 concludes.

2 Facts on Labor Market Power

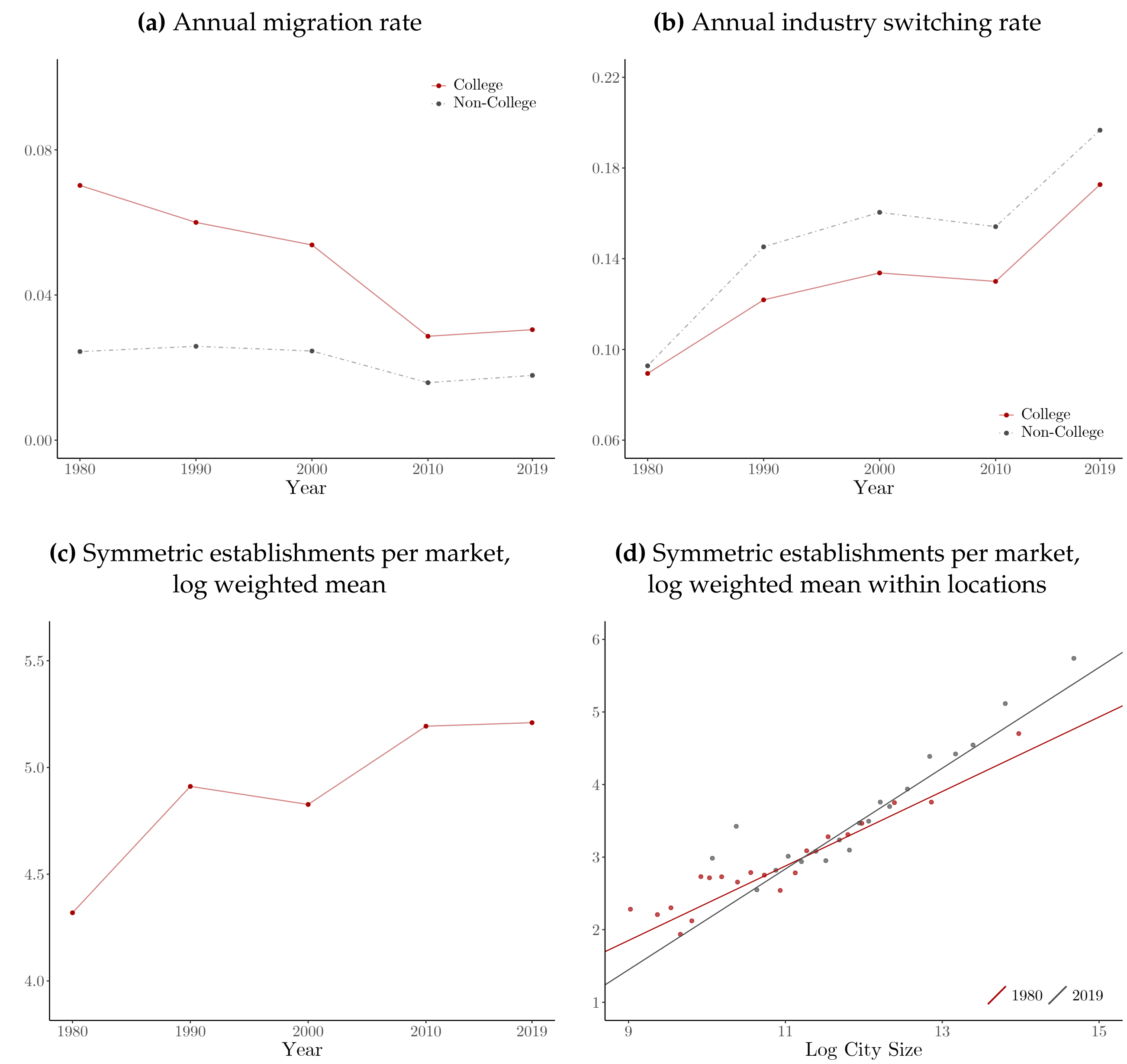
Figure 1 illustrates how a set of potential contributors to local labor market power have evolved over time. First, annual migration rates have declined (Panel 1a), especially among college-educated workers. Lower mobility strengthens the spatial segmentation of labor markets and tends to increase monopsony power. Second, job switching across industries has risen sharply (Panel 1b). Greater cross-industry mobility increases the effective set of employment options available to workers within a given location, reducing firms' ability to ex-

[3]Papers examining housing policy in a spatial context, particularly regulatory constraints on housing supply in major urban areas, include Ganong and Shoag (2017) and Hsieh and Moretti (2019). Similar to our approach, Diamond (2016) estimate workers' preferences for cities using a two-step estimator following Berry, Levinsohn and Pakes (1995).

[4]Conceptually similar to our geographic mobility friction, Vial Lecaros, Zárate and Pérez Pérez (2023) and Datta (2024) model commuting costs as a source of local labor market power within metropolitan areas.

[5]Another related paper is Azar, Berry and Marinescu (2022), who estimate the degree of labor market power in the U.S. using a nested logit model.

Figure 1: Trends in potential contributors to labor market power



Notes: Data for Panel (a) are drawn from the U.S. Census (1980–2019); for Panel (b) from the CPS (1980–2017); for Panels (c) and (d) from the CBP (1980–2016). Averages in Panels (c) and (d) are weighted by employment. In Panel (d), locations are grouped into ventiles of city size to improve visual clarity. The plotted values represent the mean number of establishments within each group of locations. "Symmetric" establishments refer to the hypothetical number of equally-sized establishments that would yield the observed local employment concentration (Adelman 1969).

ercise labor market power. Third, the number of establishments per location–industry has increased (Panel 1c).[6] More local employer competition also pushes markdowns downward. This growth in establishments reflects two forces. Workers have become increasingly concentrated in larger cities, which host more firms on average (Panel 1d); moreover, the number of establishments has also risen within location–industry markets (Appendix Figure D1). Taken together, falling migration rates, rising industry switching, and rising firm counts work in

[6] We plot "symmetric" establishments, i.e., the hypothetical number of equally sized establishments implied by the observed employment concentration levels, computed as the reciprocal of the employment Herfindahl–Hirschman Index (Adelman 1969).

opposite directions, making the overall effect on local labor market power theoretically and quantitatively ambiguous.

Investigating the underlying determinants of the decline in migration and the rise in industry-switching lies beyond the scope of this paper. Instead, these phenomena are treated as inputs in the model and are captured via exogenous time-varying migration and switching costs, except to the extent that they are accounted for by the model's equilibrium outcomes (e.g., differential wage and rent dynamics between large and small cities). There exists a large literature on the decline in internal migration (Jia et al. 2023), linking the trend to factors such as the growing prevalence of dual-earner households, which could reduce family-level mobility due to coordination problems, or lower returns to relocating.

By contrast, the increase in switching across industries is comparatively under-documented in the literature. One plausible explanation, as illustrated in Appendix Figure D2, is that the "task distance" between industries, measured by differences in routine, abstract and manual task content, has gradually declined over time among college-educated workers. As occupations have evolved, they increasingly span a broader range of industries. Using CPS data from 1980–2017, we find that the dispersion of occupational employment across industries, as measured by the variance of log industry employment within occupations, has doubled for the average college-educated worker and risen by 63.3% for the average non-college worker.

Finally, as shown in Appendix Figure D3, annual industry-switching rates by education group evolve similarly over time in small and large locations. This supports the modeling choice to treat the industry decision as distinct from the location decision, which, as discussed in Section 4.2, is a simplification that is necessary to preserve tractability.

3 Model

We build a model of worker sorting across locations and industries with strategic competition for labor among firms. Workers can move across locations or switch across industries upon paying a utility cost of moving and switching. A finite number of firms in each location-industry produce a homogeneous good using skilled and unskilled labor. In demanding labor, firms act as Cournot players in their local labor markets. The utility costs of moving and switching determine the extent to which the Cournot players are able to reduce wages below the competitive level.

3.1 Workers and Labor Supply

Workers are characterized by their initial location j, industry k, and their educational type $e \in \{n, c\}$. We treat the educational type as a fixed individual characteristic: n and c stand for "non-college educated" and "college educated". Workers choose in which location j' to live and in which industry k' to work. The units of choice are metropolitan areas and three-digit industries. They receive after-tax wages $w^e_{j'k't}$ and pay rent $r_{j't}$ per unit of housing.

If they choose to move from j to a different location $j' \neq j$, or switch industries $k' \neq k$, they pay the utility cost of moving $\mu_t^e(j, j')$ and switching $\delta_t^e(k, k')$. They derive utility from numeraire consumption c, housing consumption h, and local amenities $\xi_{j'k't}$ in their respective locations and industries of choice. Additionally, each worker i receives random utility $\varepsilon_{ij'k't}$ from choosing j' and k'. We assume that $\varepsilon_{ij'k't}$ follow a Type 1 EV distribution.

$$\begin{aligned} \max_{c,h,j',k'} u_i(c, h, j', k' \mid j, k) &= \beta_c \log(c) + \beta_h \log(h) + \xi^e_{j'k't} - \mu_t^e(j, j') - \delta_t^e(k, k') + \varepsilon_{ij'k't} \\ &\text{s.t.} \quad c + r_{j't} \cdot h \leq w^e_{j'k't}. \end{aligned} \tag{1}$$

Parameter $\mu_t^e(j, j')$ captures the total utility cost of moving and will be parameterized as a function of physical distance. Similarly, $\delta_t^e(k, k')$ captures the utility cost of switching industries and is a function of task distances. We allow these costs to vary by education type and over time. Conditional on having chosen location j' and industry k', maximizing the utility function in equation (1) subject to the budget constraint yields that expenditure on housing is a constant share of income:

$$r_{j't} h^* = \frac{\beta_h}{\beta_c + \beta_h} w^e_{j'k't}. \tag{2}$$

Plugging optimal housing consumption and optimal private consumption $c^* = \frac{\beta_c}{\beta_c+\beta_h} w^e_{j'k't}$ into utility in equation (1) generates the following indirect utility function

$$\begin{aligned} & v^e_{ij'k't}(w^e_{j'k't}, r_{j't}, \xi^e_{j'k't}, \varepsilon_{ij'k't} | j, k) \\ = \;& \beta_w \log(w^e_{j'k't}) + \beta_r \log(r_{j't}) + \xi^e_{j'k't} - \mu_t^e(j, j') - \delta_t^e(k, k') + \epsilon_{ij'k't}, \end{aligned} \tag{3}$$

where $\beta_w \equiv (\beta_c + \beta_h)$ and $\beta_r \equiv -\beta_h$. Notice that we have omitted inconsequential constants. Housing demand can be written as

$$h^* = -\frac{\beta_r}{\beta_w} \frac{w^e_{j'k't}}{r_{j't}}.$$

Since ε_{ijkt} follows a standard Type 1 EV distribution, the probability that a type e individual with initial location j and industry k chooses location j' and industry k' is given by the following expression:

$$p^e_{ij'k't}(j, k) = \frac{\exp\left(\beta_w \log(w^e_{j'k't}) + \beta_r \log(r_{j't}) + \xi^e_{j'k't} - \mu_t^e(j, j') - \delta_t^e(k, k')\right)}{\sum\limits_{j'',k''} \exp\left(\beta_w \log(w^e_{j''k''t}) + \beta_r \log(r_{j''t}) + \xi^e_{j''k''t} - \mu_t^e(j, j'') - \delta_t^e(k, k'')\right)}. \tag{4}$$

Notice that choice probabilities are a function wages and rents not only in location j' and industry k' but all other locations and industries. We aggregate these choice probabilities across all individuals of type e and initial location-industries (j, k) to obtain total labor supply N in location j' and industry k':

$$N^e_{j'k't}(w^e_{j'k't}) = \sum_{i}^{N^e} p^e_{ij'k't}(j, k). \tag{5}$$

One can then derive the labor supply elasticity (see Appendix Section A.1):

$$\eta^e_{j'k't} = \frac{\partial N^e_{j'k't}}{\partial w^e_{j'k't}} \frac{w^e_{j'k't}}{N^e_{j'k't}} = \frac{\beta_w}{N^e_{j'k't}} \sum_{i=1}^{N^e} p_{ij'k't}(1 - p_{ij'k't}). \tag{6}$$

Intuitively, the labor supply becomes more elastic, i.e., workers respond more strongly to wage changes, when the marginal utility of wages β_w is higher.

3.2 Firms and Labor Demand

In each location-industry (j, k) there are m_{jkt} symmetric firms which produce a homogeneous good by combining two types of labor: college-educated n^c and non-college educated n^n. Firm entry into a location-industry is free. Firms are symmetric within location-industries, but differ across location-industries in total factor productivities A_{jkt} and factor shares θ^e_{jkt}. Fixed costs of entry F_{jkt} vary across markets. Due to our assumptions on the workers' discrete choice problem, the labor supply curves in each location-industry are smoothly upward sloping. The higher the wages in a given location-industry, the more workers decide to move in and switch in from other location-industries. Firms engage in Cournot competition for the workers of both types at their local level, taking as given the equilibrium wages in all other location-industries at the national level, and taking as given how worker sorting responds to wages paid in (j, k). The firms' problem is given by

$$\max_{n^c,\, n^n} \; \pi_{jkt} = A_{jkt}\, \mathcal{N}(n^c, n^n) - w^c_{jkt}(n^c, N^c_{jkt})\; n^c - w^n_{jkt}(n^n, N^n_{jkt})\; n^n - F_{jkt}, \tag{7}$$

where $\mathcal{N}(n^c, n^n)$ is a standard CES aggregator of the two types of labor:[7]

$$\mathcal{N}(n^c, n^n) = \left(\theta^c_{jkt} \cdot (n^c)^{\frac{\rho-1}{\rho}} + \theta^n_{jkt} \cdot (n^n)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}. \tag{8}$$

Notice that the inverse labor supply functions $w^c_{jk}(N^c_{jk})$ and $w^n_{jk}(N^n_{jk})$ in each location-industry stem directly from the worker's problem, given by the inverse of equation (5). The total labor demand in location-industry (j, k) is the sum of labor demand across the m_{jkt} firms:

$$\begin{aligned} N^n_{jkt} &= m_{jkt} n^n \\ N^c_{jkt} &= m_{jkt} n^c. \end{aligned} \tag{9}$$

The extent of firms' local labor market power depends on the number of competitors m_{jkt} and on workers' labor supply elasticity. In particular, wages in each location-industry are given by the education-specific first order conditions:

$$w^e_{jkt} = \underbrace{\frac{m_{jkt}\left(\eta^e_{jkt}\right)^{-1}}{1 + m_{jkt}\left(\eta^e_{jkt}\right)^{-1}}}_{1\,-\,\text{Markdown}} \text{MPL}^e_{jkt}, \tag{10}$$

[7] We restrict $\theta^c_{jkt} + \theta^n_{jkt} = 1$, as is typical.

where $\text{MPL}^e_{jkt} = A_{jkt}\left(\theta^c_{jkt}\cdot(n^c)^{\frac{\rho-1}{\rho}} + (1-\theta^c_{jkt})\cdot(n^n)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}\theta^e_{jkt}\cdot(n^e)^{-\frac{1}{\rho}}$ is the marginal product of labor and $\left(\eta^e_{jkt}\right)^{-1}$ is the inverse labor supply elasticity. With perfect competition, wages are equal to the marginal product of labor and markdowns are zero. This happens if either the number of firms is arbitrarily large ($m_{jkt}\to\infty$) or if labor supply is perfectly elastic ($\left(\eta^e_{jkt}\right)^{-1}\to 0$), which occurs when moving and switching costs are negligible or when the marginal utility of wages, β_w, is very high.

The number of firms m_{jkt} per location-industry-year is endogenous to a free-entry condition specific to each market. In the counterfactual exercises, we allow the productivity of firms to adjust with local employment sizes through agglomeration economies (Duranton and Puga 2004). These agglomeration economies are not internalized by firms and are assumed to follow the linear relationship

$$A_{jkt} = \alpha_{jkt} + \lambda\log\textstyle\sum_j\sum_k(N^n_{jkt}+N^c_{jkt}), \tag{11}$$

where λ captures the strength of agglomeration economies. Because free entry requires equilibrium profits to satisfy $\pi^*_{jkt} = F_{jkt}$, increases in city size that raise productivity and profits in the counterfactual scenarios induce additional firm entry, which continues until profits are again driven down to the exogenous entry cost F_{jkt}.

Taxes The government raises revenue by taxing labor income to finance public goods, which do not affect individuals' marginal propensity to consume, and to carry out spatial policies (see Section 6). Given mean gross wages $\overline{w}_t$, the average tax rate at gross wage level w^e_{jkt} is given by:

$$T_t(w^e_{jkt}) = 1 - \varsigma_0\left(\frac{w^e_{jkt}}{\overline{w}_t}\right)^{-\varsigma_1}$$

This formulation of the income tax function is standard in the literature (Bénabou 2002, Guner, Kaygusuz and Ventura 2014). The parameter ς_0 determines the average tax level, while ς_1 determines the progressivity.

3.3 Housing Markets

Housing demand h^D in location j equals the sum of housing demand of workers in location j, aggregated across industries k:

$$h^D_{jt} = \sum_k N^n_{jkt}\frac{-\beta_r w^n_{jkt}}{\beta_w r_{jt}} + \sum_k N^c_{jkt}\frac{-\beta_r w^c_{jkt}}{\beta_w r_{jt}}. \tag{12}$$

We model housing supply as upward sloping with location-specific constant elasticities and intercepts, following Saiz (2010). The inverse housing supply function is specified with constant location-specific elasticities γ_{jt}:

$$r_{jt} = \kappa_{jt}\left(h^S_{jt}\right)^{\gamma_{jt}} \tag{13}$$

The intercept κ_{jt} may reflect location-specific construction costs, whereas variation in the inverse housing supply elasticity γ_{jt} could stem from differences in developable land and local regulatory constraints.[8] As part of the counterfactual, we analyze how increasing housing supply elasticities in big cities affects the spatial distribution of wage markdowns.

3.4 Equilibrium

An equilibrium is a distribution of workers across locations and industries, sets of wages and rents, and tax rates such that local labor markets clear for both types of labor, firms' labor demand is an equilibrium of the augmented Cournot game within each local labor market, housing markets clear, no worker wishes to move or switch industries, and the government budget is balanced. We provide a full definition in Appendix Section A.3.

4 Estimation

Our estimation proceeds in three steps. First, we recover migration and industry-switching costs using a BLP procedure based on individuals' discrete choices over local labor markets (Berry, Levinsohn and Pakes 1995, Bayer, Keohane and Timmins 2009). Second, we identify the marginal utilities of wages and rents by instrumenting their changes with a shift–share IV that exploits labor-demand variation induced by free trade agreements with Canada and Mexico (CUSFTA and NAFTA). Third, we estimate the remaining housing and labor-market parameters by inverting the model's equilibrium conditions to exactly match observed wages and housing prices, and internally calibrate unobserved amenities to replicate the allocation of workers across locations and industries.

4.1 Data

In this section, we document the data sources used for the model inputs. Further details are provided in Appendix Section B.1. Table 1 reports summary statistics for all the listed variables.

Labor Supply We use the 5 percent samples of the US Census 1980-2000 and the ACS 5-year samples from 2007-2011 and 2015-2019 for information on individual location choices, industry choices, wages, rents, and education.[9] Locations are defined as a metropolitan statistical area, and industries follow the 3-digit Census industry classification.

Movers are defined as individuals who have moved across locations during the last year. For movers, we define the location in which they lived one year ago as their initial location and the current location as the observed optimal choice. For non-movers, the initial location

[8]Function (13) can be obtained from the first-order condition of a representative construction firm that operates with a convex cost technology (Kaas et al. 2021).

[9]We focus on full-time employed individuals aged 20 to 65, earning non-zero wages, who are not institutionalized and not in the military. We group individuals by educational attainment "college degree" versus "no college degree".

and observed optimal location coincide.[10] In Census data up to 2000, migration is instead measured over a five-year window. To ensure consistency, we convert these 5-year migration rates to a 1-year equivalent by exploiting the 2000 Census, which provides both 1-year and 5-year state-level migration data. From this, we compute state-specific ratios of five-year to one-year migration and, assuming this relationship remains stable within states over time, apply these ratios to earlier decades to interpolate one-year migration rates for 1980 and 1990.

Industry switchers are individuals who have switched jobs to another 3-digit industry in the past year. While the current industry of individual employment is recorded in the Census and ACS data, there is no information on previous industries in which individuals might have worked. Therefore, we use information from the Current Population Survey (CPS) 1975-2017 to observe switching choices across 3-digit Census industries.[11] Jointly, locations and industries constitute the choice set for workers in our model, and previous location, previous industry, and educational group constitute the state variables. Since we focus on location and industry choices within one year, we treat educational attainment as a fixed individual characteristic.

Wages in each location-industry are measured as fixed effects per location-industry, conditional on a set of individual observables to eliminate potential confounding from differences in demographic composition. Location-level wages, required for the estimation procedure described in Section 4.2, are obtained as location fixed effects conditional on industry fixed effects. Similarly, industry-level wages are estimated conditional on location fixed effects. Rents in each location are measured as the annualized user cost of housing, conditional on housing characteristics. We follow the literature closely in constructing these, and hence relegate the details to Appendix Section B.1.

Labor Demand To quantify the degree of Cournot competition on the labor demand side, we compute the number of employers per location–industry as "symmetric" equivalents, following Adelman (1969). This represents the hypothetical number of equally-sized establishments that would generate the observed local employment concentration levels, and is obtained as the reciprocal of the employment Herfindahl–Hirschman Index (HHI). Formally, the symmetric number of establishments in each market is defined as

$$m_{jkt} = \frac{1}{\mathrm{HHI}_{jkt}} = \left(\sum_{l=1}^{M_{jkt}} s_{ljkt}^2 \right)^{-1} \tag{14}$$

where s_{ljkt} denotes the employment share of establishment l in location–industry (j, k) at time t, within a market containing M_{jkt} (potentially asymmetric) establishments.

We measure m_{jkt} using the County Business Patterns (CBP) 1980-2016, an annual series published by the U.S. Census Bureau that reports the number of establishments with paid employees, disaggregated by county, industry, and employment-size class (i.e., 1–4, 5–9, 10–19,

[10] We drop individuals who lived abroad before their move.

[11] We pool multiple years to increase sample size: 1975–1984 for 1980, 1985–1994 for 1990, 1995–2004 for 2000, 2005–2014 for 2010, and 2015–2017 for 2019.

Table 1: Summary statistics

	Observations	Mean	SD	Min	Max
Prices					
ln Non-college wage	111,003	10.362	0.430	8.257	13.438
ln College wage	111,003	10.778	0.573	8.101	13.701
ln Rent	111,003	9.395	0.492	8.125	10.780
Labor Demand					
Establishments (symmetric)	111,003	24.052	90.826	1.000	6,949.431
Labor Supply: Choice set					
Locations	219				
Industries	177				
Location-industries	31,635				
Task distances non-college	31,329	1.592	0.835	0.000	5.589
Task distances college	31,329	1.279	0.820	0.000	6.433
Labor Supply: Choices					
Annual moving non-college	1,079	0.028	0.020	0.000	0.269
Annual moving college	1,079	0.070	0.051	0.000	0.350
Annual switching non-college	1,137	0.166	0.061	0.000	0.394
Annual switching college	1,137	0.162	0.080	0.000	0.835
Housing Supply					
Elasticity	1,078	2.235	1.184	0.595	7.842
Share land unavailable	1,078	0.272	0.198	0.004	0.883

Notes: Data sources include U.S. Census 1980, 1990, 2000, ACS 2007-2011, 2015-2019, CPS 1975-2017, and DOT 1977. Housing cost annualized for owners. Mean number of employers are unweighted averages of equivalent symmetric firms per location-industry, based on CBP 1980-2016 data. Switchers are calculated across industries. Housing supply elasticities are drawn from Saiz (2010), and land unavailability data from Lutz and Sand (2023).

20–49, 50–99, 100–249, 250–499, 500–999, 1000–1499, 1500–2499, 2500–4999, and 5000+ workers). We assign each establishment a number of workers corresponding to the midpoint of its employment-size interval (e.g., 2.5 workers for the 1–4 bin, 7 for 5–9, and so on), and map counties to their corresponding metropolitan areas to compute the Herfindahl–Hirschman Index (HHI) by industry–location for each year. Because data for smaller counties are heavily censored after 2017, we use 2016 data to represent the 2019 decade. The number of symmetric establishments is then computed according to equation (14).

Task Distance To measure task distances across industries, on which cross-industry switching costs depend, we follow the approach of Autor and Dorn (2013). Specifically, we use the Dictionary of Occupational Titles (DOT 1977) to assign each occupation a score for routine, abstract, and manual tasks. We then aggregate these occupation-level measures to the industry level using decade-specific employment weights, so that each industry is represented by a vector of routine, abstract, and manual task intensities. Finally, we compute the Euclidean distance between industry task vectors to quantify the task distance between each pair of industries.

Housing Supply Metropolitan area–specific estimates of housing supply elasticities are taken from Saiz (2010). We complement these with county-level data on the share of land unavailable for development from Lutz and Sand (2023), which we aggregate to the location level using population-weighted averages. Both variables are used in the construction of the shift-share instrumental variables for housing prices, as described in Section 4.3.

4.2 Labor Supply Parameters

In this section, we describe how we estimate the structural labor supply parameters in equation (3), based on individuals' discrete choice over locations and industries in a two-stage BLP estimation procedure (Berry, Levinsohn and Pakes 1995, Bayer, Keohane and Timmins 2009).

Utility function parameters In the first step, the parameters of interest are the marginal utility of wages β_w and rents β_r, and the parameters of the utility cost functions of moving across locations μ. The identifying variation in the data are the observed location choices, given location-specific wages, rents, educational types, and previous location choices. In a separate step, we estimate the utility cost of switching jobs across industries. This separation is necessary because the data does not allow us to jointly observe current and previous location-industry choices.[12] Notice that even if we were able to observe the current and previous location-industry choice jointly, it would be computationally challenging to solve a system with $200 \times 300 = 60{,}000$ possible states and choices. Finally, we bring the estimates together by setting location-industry specific unobserved utilities ξ^e_{jkt} such that the observed allocations of workers across locations and industries in each year t constitute a sorting equilibrium.

The observed location choice shares by educational type and initial locations are matched to choice probabilities from the model to estimate v^e_{jt} and $\mu^e_t(j, j')$. Given the Type I EV distribution assumption for individual idiosyncratic preferences, the model choice probabilities are given by:

$$p^e_t(j' \mid j) \quad = \quad \frac{\exp(\overbrace{\beta_w \log(w^e_{j't}) + \beta_r \log(r_{j't}) + \xi^e_{j't}}^{=v^e_{j't}} - \mu^e_t(j, j'))}{\sum_{j''} \exp\left(\beta_w \log(w^e_{j''t}) + \beta_r \log(r_{j''t}) + \xi^e_{j''t} - \mu^e_t(j, j'')\right)} \tag{15}$$

We use flexible specifications for the utility cost of moving across locations across industries, and we allow these costs to vary across educational types e and over time. Equation (16) parameterizes the utility cost of moving as a piecewise constant function of physical distance, thereby accommodating plausible non-linearities in distance. $I_{100}, I_{500}, \ldots$ are indicators for

[12] Reassuringly, annual industry-switching rates within education groups exhibit similar patterns in small and large cities, as shown in Appendix Figure D3. Consistent with the separation in the estimation procedure, location-level wages used in the migration choice are estimated controlling for industry fixed effects, while industry-level wages used in the industry-switching choice are estimated controlling for location fixed effects (see Appendix Section B.1).

whether the distance between locations j and j' is higher than 100 km, 500 km, etc.[13]

$$\begin{aligned}\mu_t^e(j,j') \quad &= \quad \mu_{100,t}^e\, I_{100}(j,j') + \mu_{500,t}^e\, I_{500}(j,j') + \mu_{1000,t}^e\, I_{1000}(j,j') \\ &\quad +\mu_{1500,t}^e\, I_{1500}(j,j') + \mu_{2000,t}^e\, I_{2000}(j,j')\end{aligned} \tag{16}$$

We estimate this first stage by Maximum Likelihood with a Berry contraction mapping separately for each educational type e and year t, based on the choice probabilities in equation (15). This procedure is standard in the literature (Bayer, Keohane and Timmins 2009, Mathes 2025). In the log-likelihood function, $I(j(i),j')$ is an indicator equal to 1 if the individual i who previously chose location j now chooses location j':

$$\max_{v_{j't}^e,\mu_t^e} \mathcal{LL}_t^e = \sum_{i\in N^e} I\left(j(i),j'\right)\ \log\left(p_t^e(j' \mid j(i))\right) \quad \forall e\in\{n,c\} \tag{17}$$

In the second stage, we decompose the estimated mean utility values $v_{j't}^e$ on location specific wages and rents to recover the marginal utility parameters β_w and β_r. We take differences to eliminate time-invariant unobservables, and use shift-share instruments to isolate exogenous variation in these differences (see Section 4.3):

$$\Delta v_{j't}^e = \beta_w \Delta \log(w_{j't}^e) + \beta_r \Delta \log(r_{j't}) + \Delta \xi_{j't}^e \quad \forall e\in\{n,c\} \tag{18}$$

Analogous to the utility cost of moving, we estimate the mean utility of working in industry k, ξ_{kt}^e, as well as the utility cost of switching across industries δ_t^e. The switching costs vary by educational group e and over time, and are parameterized as a function of the task distance between industries:

$$\begin{aligned}\delta_t^e(k,k') \quad &= \quad \delta_{0.05,t}^e\, I_{0.05}(k,k') + \delta_{0.3,t}^e\, I_{0.3}(k,k') + \delta_{0.8,t}^e\, I_{0.8}(k,k') \\ &\quad +\delta_{1.5,t}^e\, I_{1.5}(k,k') + \delta_{2,t}^e\, I_2(k,k') + \delta_{4,t}^e\, I_4(k,k'),\end{aligned} \tag{19}$$

where $I_{0.05}, I_{0.3}, \ldots$ are indicator variables denoting whether the Euclidean task distance between industries k and k' is above 0.05, above 0.3, and so on.

We complete the estimation by combining the parameters β_w, β_r, μ_t^e, and δ_t^e to calibrate the joint unobserved utility term $\xi_{j'k't}^e$ in equation (4). This is done through a fixed-point iteration procedure ensuring that the observed allocation of workers across locations and industries constitutes an equilibrium allocation. In this context, an equilibrium allocation are observed choice shares that constitute a fixed point of the utility maximization problem. The calibration uses the location–industry wage fixed effects $w_{j'k't}^e$ (see Appendix Section B.1).

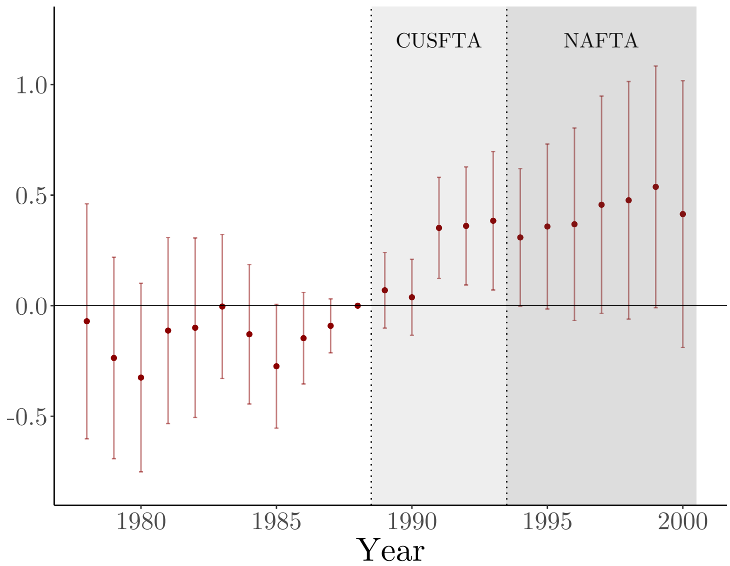
[13]For each metropolitan area in our sample, we find the geographic center from Census Bureau shapefiles and compute the pairwise distances in kilometers.

4.3 IV Estimation

We estimate the coefficients β_w and β_r in equation (18), which are key determinants of labor supply elasticity (see equations 6 and 24) and, consequently, of the degree of labor market power (see equation 10). A typical concern when estimating equation (18) is that time-varying unobserved location-specific amenities may be correlated with changes in rents and wages, leading to omitted variable bias in the estimation of β_w and β_r. To address this issue and isolate plausibly exogenous variation in wages and rents over time, we construct a novel shift–share instrument based on changes in labor demand induced by import competition following the Canada–U.S. and North American Free Trade Agreements (CUSFTA and NAFTA).

CUSFTA and NAFTA, implemented in 1989 and 1994, respectively, dramatically reduced trade barriers between Canada, the United States, and later Mexico. These agreements triggered a sharp expansion in cross-border trade flows beginning in the late 1980s, and altered the composition of labor demand across industries with differential exposure to import competition. Figure 2 illustrates this evolution by plotting how the log value of imports from Canada and Mexico (relative to imports from the rest of the world) evolves over time. Before 1988, there is no systematic difference, but following the implementation of CUSFTA and especially NAFTA there is a clear and persistent increase in the relative value of imports from these partner countries. The timing of these institutional shocks therefore provides plausibly exogenous time-series variation that we exploit to construct our shift–share instrument.

Figure 2: Log imports value from Canada and Mexico (relative to the rest of the world)



Notes: The figure plots year-by-treatment fixed effects from a regression where the outcome variable is the log value of imports. The treatment is defined as imports originating from Canada and Mexico; the control group is imports from the rest of the world. All specifications also include year, treatment, and country fixed effects. Data: Schott (2008), U.S. Census Bureau.

The shift–share instrument combines 1980 industry employment shares in location j and education group e with changes in the industry-level log value of imports from Canada and

Mexico between 1980 and 2000:

$$Z_1 = \sum_{k=1}^{K} s_{ejk,1980} \Delta \text{log Imports}_{jk,1980-2000}$$

We use pre-determined 1980 base shares, which mitigates concerns that local employment composition may itself respond to contemporaneous trade shocks. The "shift" component comes from long-run changes in industry-level import values from Canada and Mexico induced by the trade liberalizations, while the "share" component captures differential baseline exposure across local labor markets.

Z_1 is the shift–share instrument used for log wages. For housing prices, we allow the same import-driven shock to propagate heterogeneously across locations by interacting this instrument with ψ_j and LandUnav_j – the inverse housing supply elasticity and the share of land unavailable for development in location j (see Section 4.1). Formally:

$$Z_2 = \psi_j \sum_{k=1}^{K} s_{ejk,1980} \Delta \text{log Imports}_{jk,1980-2000}$$
$$Z_3 = \text{LandUnav}_j \sum_{k=1}^{K} s_{ejk,1980} \Delta \text{log Imports}_{jk,1980-2000}.$$

This allows the same import-driven labor demand shock to translate into heterogeneous predicted housing price responses across locations. In markets with tighter supply constraints, either because housing supply is highly inelastic (high ψ_j) or because a large share of land is unavailable for development, identical shocks translate into larger predicted price increases, whereas locations with elastic housing supply experience smaller effects. Consistent with the time frame of the instrument, we restrict the long difference version of the utility function that we estimate (equation 18) to years 1980 and 2000:

$$v^e_{j2000} - v^e_{j1980} = \alpha_e + \beta_w(\log w^e_{j2000} - \log w^e_{j1980}) + \beta_r(\log r^e_{j2000} - \log r^e_{j1980}) + \beta \mathbf{x}_{jt} + \epsilon_{jt} \quad (20)$$

The exogeneity of these IVs are driven by the shifts rather than the shares (Borusyak, Hull and Jaravel 2024). The shares may still embed endogenous local characteristics, such as labor reallocation across industries linked to other unobservables, or heterogeneity in housing supply elasticity that is typically correlated with amenities and other housing demand factors (Davidoff 2016). Following Borusyak, Hull and Jaravel (2024), we address this concern by "recentering" the instrument, i.e. controlling for the local sum of shares, so that identification only comes from the quasi-random national component of the trade shocks.

To support the plausibility of the exogeneity assumption for the industry-level shifts, we first note the absence of differential pre-trends in log import values from Canada and Mexico compared to the rest of the world prior to the trade liberalizations (see Figure 2). Moreover, Appendix Table D1 documents that the national import shocks are not systematically related to changes in industry-level worker composition along key labor supply dimensions such as age, gender, or race. The shifts are only marginally correlated with changes in the share of international migrants, so we explicitly account for this potential confounder in the IV specification, weighting the migration measure by exposure shares as described in Borusyak, Hull and Jaravel (2024).

Table 2: OLS and IV estimates of labor supply parameters

		Δ Mean Utility Locations	
		(1)	(2)
Δ Log Wage		1.236^{***}	6.977^{***}
		(0.3036)	(2.385)
Δ Log Rent		0.4401^{**}	-2.261^{*}
		(0.1996)	(1.366)
Controls:	College FEs	✓	✓
	City Amenities	✓	✓
	Local Sum of Shares		✓
	International Migration		✓
Observations		438	438
Estimation Method		OLS	IV
F-test (First Stage, Δ Log Wage)		–	8.12
F-test (First Stage, Δ Log Rent)		–	5.56

Notes: The table reports estimates of equation (20). Column (1) presents OLS estimates, while column (2) reports IV estimates. All specifications include college fixed effects, city amenities, the local sum of exposure shares, and changes in international migration at the industry level weighted by local exposure shares (Borusyak, Hull and Jaravel 2024). Heteroskedasticity-robust standard errors in parentheses. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

The estimated coefficients for β_w and β_r in equation (18) are reported in Table 2. The OLS estimates in column (1) suggest that both higher wages and higher rents are positively associated with changes in mean utility. The positive coefficient on rents is counterintuitive: in principle, higher housing costs should reduce worker utility. A plausible interpretation is that OLS is confounding causal price effects with unobserved amenities: places that become increasingly attractive also experience higher rents, which mechanically loads onto the utility regression despite the inclusion of our amenity index based on PCA (Diamond (2016), see Appendix Section B.1).

By contrast, the IV estimates in column (2) yield the theoretically consistent signs. Higher wages significantly raise utility, while higher rents reduce it. Moreover, the magnitudes of (β_w, β_r) are broadly in line with those obtained by Diamond (2016), where β_w ranges from 3.26 to 4.98 and β_r ranges from -2.94 to -2.16 in a comparable specification. The fact that we recover similar values despite using a different exogenous variation – import-driven shift shocks rather than national industry growth rates – provides additional external validation for our empirical approach. Appendix Table D2 reports the first stage results.

Diagnostics As a robustness check, we estimate a placebo version of equation (20) in which we replace the left-hand side with the change in mean utility between 2010 and 2000 (rather than 2000–1980, the relevant time horizon for the IV):

$$v^e_{2010} - v^e_{j2000} = \alpha_e + \beta_w(\log w^e_{j2000} - \log w^e_{j1980}) + \beta_r(\log r^e_{j2000} - \log r^e_{j1980}) + \beta \mathbf{x}_{jt} + \epsilon_{jt} \quad (21)$$

If the IV is truly isolating exogenous variation in labor demand shocks, as opposed to spurious correlations, the placebo regression should deliver coefficients that are statistically indistinguishable from zero. This is exactly what we find (Appendix Table D3).

Finally, the number of independent shifts embedded in the shift–share IV is sufficiently large for the "many uncorrelated shocks" condition of Borusyak, Hull and Jaravel (2024) to plausibly hold: the implied Herfindahl-Hirschman Index of the shares is 0.06, corresponding to roughly 16.7 effectively distinct shocks.

4.4 Housing and Labor Demand Parameters

Given the labor supply parameters estimated in Sections 4.2 and 4.3, we recover the implied distribution of labor supply elasticities across education groups and local labor markets (equation 6). Using the observed equilibrium allocation of workers across industries and locations, we then have closed-form expressions for equilibrium wages and housing prices. Specifically, wages follow from the firms' first-order condition in equation (10), after substituting the labor supply vector into labor demand, while housing prices are determined by equation (13), after substituting housing demand into housing supply.

We invert these equilibrium conditions to recover the structural parameters that rationalize the set of housing prices and wages observed in the data. In particular, we estimate the distribution of housing supply intercepts κ_{jt} and productivity parameters θ^c_{jkt} and A_{jkt} such that equilibrium wages and housing prices from the model exactly match their empirical counterparts in each location–industry cell. Further details on the estimation procedure are provided in Appendix Section B.2. Finally, using the estimated productivity terms A_{jkt}, we quantify the strength of agglomeration economies by estimating the regression form of equation (11), as captured by the elasticity parameter λ.

4.5 Parameters

Table 3 summarizes the model parameters. Some parameters are drawn from the literature, including the CES production elasticity ρ (Card 2009), the inverse housing supply elasticities ψ_j (Saiz 2010), and the tax function parameters $(\varsigma_0, \varsigma_1)$ from Guner, Kaygusuz and Ventura (2014). The indirect utility parameters (β_w, β_r), migration costs $\mu_{et}(j, j')$, and industry switching costs $\delta_{et}(k, k')$ are estimated using the two-step BLP procedure based on observed migration and industry-switching flows. The productivity parameters (A_{jkt}, θ_{Njkt}) and housing supply intercepts κ_{jt} are chosen to exactly replicate equilibrium wages and housing prices in the data, while the amenity terms ξ^e_{jkt} are internally calibrated to match the observed allocation of labor across local labor markets.

Table 3: Model parameters

	Parameter	Value	Source
External Parameters:			
CES production function parameter	ρ	2	Card (2009)
Inverse housing supply elasticity	ψ_j	Table 1	Saiz (2010)
Tax function	$(\varsigma_0, \varsigma_1)$	(0.902,0.036)	Guner, Kaygusuz and Ventura (2014)
Indirect utility parameters	(β_w, β_r)	(6.977,−2.261)	Data
Migration costs	$\mu_{et}(j, j')$	Table D4	Data
Industry switching costs	$\delta_{et}(k, k')$	Table D5	Data
Agglomeration elasticity	λ	0.027	Model
Agglomeration constants	a_{jkt}	Table D6	Model
Internally Calibrated:			
Productivity	$(A_{jkt}, \theta^n_{jkt}, \theta^c_{jkt})$	Table D6	Wages
Housing supply intercepts	κ_{jt}	Table D6	Housing Prices
Amenities	ξ^n_{jkt}, ξ^c_{jkt}	Table D6	Population

Model Validation The estimated utility function parameters, and in particular the IV-based coefficient β_w, imply a median labor supply elasticity of 22.96 in 1980 and 33.49 in 2019. These values lie within the upper range of best-practice labor supply estimates reported in Sokolova and Sorensen (2021), who compile 1,320 elasticity estimates from 53 studies. In that meta-analysis, the 95% confidence interval for estimates is [2.08, 17.74] (point estimate of 9.91) and [8.29, 37.33] with a point estimate of 22.81, depending on the identification strategy.

Additional validation comes from the estimated agglomeration elasticity, $\lambda = 0.027$, which aligns with the mean and median values for U.S. studies (0.036) reported in the meta-analysis by Melo, Graham and Noland (2009), based on 184 estimates. This consistency is reassuring, as the agglomeration parameter, like β_w, is not directly targeted in the estimation procedure.

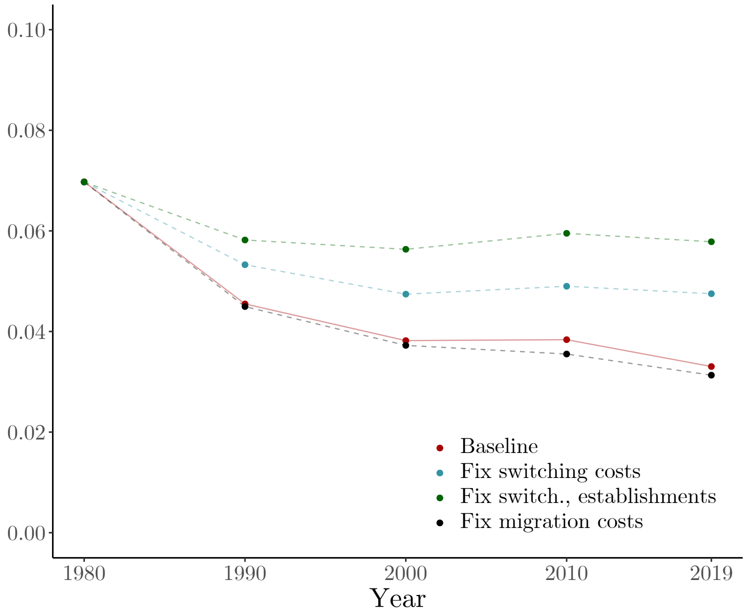
5 Labor Market Power Over Time

Given the estimated model, we compute markdowns for each local labor market using equation (10). Figure 3 displays the average markdown across location–industry cells for each decade from 1980 to 2019 (solid red line). The results indicate a pronounced decline over time: the mean markdown falls from 0.070 in 1980 to 0.033 in 2019, roughly halving over the period.

To understand the mechanisms behind this decline, we conduct a series of counterfactual exercises that progressively "shut down" specific channels in the model. First, we fix industry-switching costs at their 1980 levels. The baseline model attributes rising worker mobility across industries (Figure 1b) to declining switching costs over time. By holding these costs constant, we prevent this source of increased competition from operating. As shown by the dashed blue line in Figure 3, markdowns would then remain substantially higher, around 0.048 in 2019 instead of 0.033, suggesting that falling switching costs account for a sizable share of the observed reduction in labor market power.

Second, we jointly fix switching costs and the number of establishments per location–industry at their 1980 levels (green dashed line in Figure 3). In the baseline, the growth in the number

Figure 3: Mean markdowns across location-industries



Notes: The figure plots average markdowns across local labor markets by decade. The red line shows the baseline model, while dashed lines report counterfactual simulations fixing specific parameters to their 1980 values. See text for details.

of firms over time (Figure 1c) enhances competition among employers, contributing to the reduction in labor market power. Removing both this margin and the effect of lower switching costs keeps markdowns persistently high, around 0.057, suggesting that firm entry plays a key role in reducing monopsony power.

Finally, we isolate the role of geographic mobility by fixing migration costs across locations to their 1980 levels (black dashed line in Figure 3). In the baseline, declining migration rates over time (Figure 1a) are reflected in rising estimated migration costs (see Appendix Table D4). Reducing migration costs to their 1980 levels slightly reduces markdowns to 0.031 in 2019 compared to 0.033 in the baseline, indicating that lower geographic mobility has had only a limited quantitative effect on the long-run dynamics of labor market power.

Overall, the decline in markdowns is primarily driven by improved worker mobility across industries and intensified employer competition within local labor markets. As summarized in Table 4, reductions in industry-switching costs account for 39.4% of the overall decline in markdowns, while the expansion in the number of establishments contributes an additional 30.0%. In contrast, changes in migration costs work in the opposite direction, and fixing them to their 1980 level would imply a slightly larger reduction in markdowns (by 4.6%) than what is observed in the data.

Robustness The level of markdowns depends critically on the labor supply elasticity η_{jkt}, which is itself determined by the estimated marginal utility of wages β_w. Our baseline estimates of η_{jkt} are broadly consistent with the upper range of empirical elasticities reported in Sokolova and Sorensen (2021). As a robustness check, we recalibrate β_w to match lower-end labor supply elasticities from that meta-analysis, targeting a median elasticity of 5 in 2019.

Under this alternative calibration, mean markdowns are substantially higher in level,

Table 4: Decomposing the decline in markdowns

	Baseline	Fix Migration Costs	+ Fix Switching Costs	+ Fix Establishments
Mean Markdowns (Baseline η^e_{jkt})				
1980	0.070	0.070	0.070	0.070
2019	0.033	0.031	0.048	0.057
Contribution to markdown decline (%)	–	−4.6	39.4	30.0
Mean Markdowns (Higher η^e_{jkt})				
1980	0.265	0.265	0.265	0.265
2019	0.160	0.154	0.208	0.240
Contribution to markdown decline (%)	–	−5.7	45.7	30.5

Notes: The table reports mean markdowns across location–industry cells in 1980 and 2019 under the baseline model and under three counterfactual scenarios where parameters are fixed at their 1980 levels: industry switching costs, migration costs, and the number of establishments. The percentages reported below correspond to each channel's contribution to the overall decline in markdowns between 1980 and 2019. Negative values indicate that the channel acts in the opposite direction, amplifying the decline rather than mitigating it. The lower panel reports analogous results for the model calibrated to match higher labor supply elasticities from the literature.

0.265 in 1980 and 0.160 in 2019 (see Table 4 and Appendix Figure D4), but the dynamics remain very similar. Markdowns still decline by roughly 40% over the sample period, and the relative contributions of each mechanism are nearly unchanged: 45.7% from lower switching costs, 30.5% from increased firm entry, and −5.7% from migration costs. These results suggest that the decomposition is robust to alternative calibrations of key model parameters.

Firms may also internalize that changes in wages feed back into prices in general equilibrium, which in turn affects labor supply elasticities. Allowing firms to be sophisticated in this way yields the expression we parameterize in Appendix Section A.2. The labor supply response to a wage increase grows with the inverse housing supply elasticity and with β_r: the former amplifies the resulting rise in rents, and the latter reflects workers' sensitivity to those price increases. In practice, however, our results are virtually unchanged under this alternative assumption. Because a marginal wage change in a single industry (out of 177 in each location) generates only a negligible effect on aggregate prices in general equilibrium, the feedback mechanism remains muted.

6 Labor Market Power and Spatial Policies

We use our framework to analyze the equilibrium effects of several spatial policies. Specifically, we consider: (i) relaxing housing supply constraints in large metropolitan areas; (ii) providing migration subsidies to encourage worker relocation toward these areas; and (iii) introducing firm entry subsidies to foster competition in less competitive local labor markets.

We perform steady-state comparisons between equilibria with and without each policy in 2019. The level of labor income taxes (ς_0) adjusts endogenously, while keeping the tax progressivity parameter ς_1 fixed, to balance the government budget and finance the cost of the policy. This adjustment incorporates both changes in taxable income resulting from migration and the general equilibrium effects of the policy. Comparisons are made once prices, wages, and taxes have converged to their new steady states, abstracting from transitional dynamics.

The first two policies target the top 10% of locations by population size, corresponding to 22 metropolitan areas in our sample, while the third focuses on concentrated labor markets in the bottom 50% of the city-size distribution (110 locations). Welfare effects are expressed as the percentage change in consumption that the average newborn agent would be willing to give up, or require, to remain indifferent between the counterfactual and the benchmark equilibria. Further details on the welfare calculation are provided in Appendix Section C.1.

We conduct two versions of each counterfactual exercise. The first uses the baseline model with labor market power. The second assumes fully competitive labor markets, in which firms take wages as given and set them according to:

$$w^e_{jkt} = A_{jkt}\left(\theta^c_{jkt}\cdot(n^c)^{\frac{\rho-1}{\rho}} + (1-\theta^c_{jkt})\cdot(n^n)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}\theta^e_{jkt}\cdot(n^e)^{-\frac{1}{\rho}},$$

rather than equation (10). In this competitive version, firms do not internalize the upward-sloping nature of labor supply. Consequently, locations with low wages in the data are rationalized through lower productivity parameters A_{jkt}, whereas in the baseline model part of the same wage variation reflects positive markdowns. Since A_{jkt} is treated as exogenous and held fixed across counterfactuals, the competitive model allows us to understand how much of each spatial policy's effect in the baseline economy operates through the monopsony margin.

Increasing Housing Supply Elasticity in Large Locations Persistently high housing costs in large cities have long been a central policy concern (Glaeser and Gyourko 2002), and initiatives aimed at increasing housing supply elasticity—such as those promoting accessory dwelling units (ADUs)—have gained momentum in recent years. Several U.S. states, including Arizona, Colorado, Massachusetts, Iowa, and Washington, have recently enacted legislation to prevent local jurisdictions from restricting ADU construction through owner-occupancy requirements, parking mandates, or aesthetic regulations, following the precedent set by California.[14] In Los Angeles, ADUs accounted for approximately 30% of newly permitted housing units in 2022.[15]

To study a policy that relaxes housing supply constraints in the most supply-restricted metro areas, we reduce inverse housing supply elasticities by 5% in the top 10% largest locations. Larger cities tend to exhibit higher inverse elasticities (see Figure D5). After the policy, a city like New York achieves an elasticity level comparable to that of a considerably smaller city such as New Orleans. Table 5 reports average equilibrium effects, while Figure 4 displays heterogeneous responses across locations.

The policy induces a substantial decline in housing prices, 17.4% on average, and even larger reductions within the cities directly targeted by the reform (Figure 4a). Prices also fall in smaller cities, driven by population outflows toward newly more affordable large cities

[14] State bills: Arizona HB2720, HB2721; Colorado HB24-1152; Massachusetts Affordable Homes Act; Iowa Senate File 592; Washington HB1337; and California AB2299 and SB1069.

[15] https://bipartisanpolicy.org/blog/accessory-dwelling-units-adus-in-california/

Table 5: Policy outcomes

	Relax Housing Supply		Migration Subsidy		Firm Subsidy
	With LMP	Without LMP	With LMP	Without LMP	With LMP
Markdowns Change:					
Difference weighted mean (p.p.)	–0.0016	0	–0.0038	0	–0.0023
Average Price Changes:					
Housing prices (%)	–17.400	–17.448	1.1100	0.6175	–0.8255
Non-college wage (%)	–0.2571	–0.1021	0.4857	–0.6816	0.0605
College wage (%)	–0.4198	0.4528	–1.2096	–1.4728	–0.0452
Welfare:					
Consumption equivalence (%)	0.5651	0.5696	–0.0121	0.0153	0.0154
Taxes:					
Percentage Points Change	0	0	0.4329	0.4238	0.0148

(Figure 4b). The margins that matter for labor market power are the number of firms (Figure 4c) and labor supply elasticities (Figure 4d). Firm counts rise by roughly 5% on average, with stronger increases in large cities and mixed effects in small ones. Two forces drive these outcomes. Lower general-equilibrium wages raise firms' incentives to enter in all locations, particularly in smaller cities where wage reductions are larger. At the same time, agglomeration economies lead to productivity increases in large cities experiencing in-migration flows and productivity reductions in smaller cities with population outflows, prompting firm entry in the former and exit in the latter.

Changes in labor supply elasticities are modest and ambiguous. In large cities, lower housing prices reduce out-migration, tightening labor supply, but simultaneously attract in-migration, loosening labor supply. Lower prices in other productive cities also encourage out-migration, further increasing elasticity. In smaller cities, out-migration increases (raising elasticity), but declines in in-migration reduce elasticity. The net effect in both types of locations is therefore theoretically ambiguous and quantitatively small.

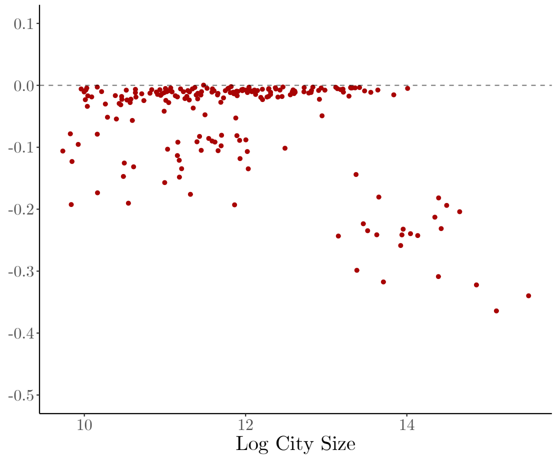
Because both firm entry and labor supply elasticities respond only weakly, the policy has limited impact on labor market power. Markdowns increase only slightly in small cities, reflecting reduced labor market competition following firm exit and are essentially unchanged elsewhere (Figure 4c). As a consequence, wages fall only marginally in small cities (Figure 4f), which also reflects weaker complementarities among workers following the substantial population outflows.

Importantly, because labor market power barely moves, the predicted effects of the policy are nearly identical in the model with and without monopsony (see Appendix Figure D6). The first two columns of Table 5 show that welfare gains are 0.565% with labor market power and 0.570% without. Modeling monopsony is therefore not essential for understanding the impact of this particular spatial policy.

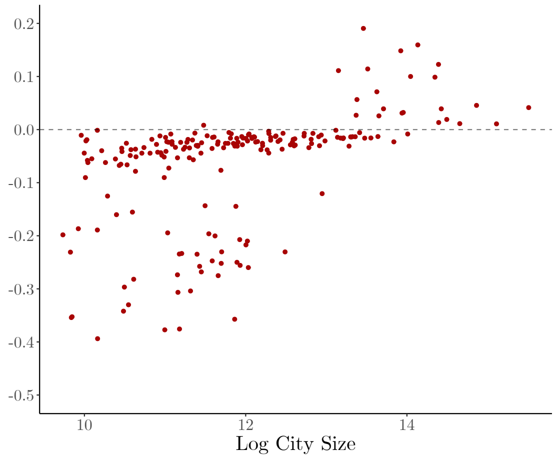
Subsidy to Move to Large Locations Since housing supply reforms have only muted effects on labor market power, a natural alternative policy lever is to subsidize migration. Moving vouchers should raise labor supply elasticities for the affected workers by effectively reducing their costs of entering other labor markets, thereby reducing markdowns. Such policies

Figure 4: Effect of 5% inverse housing supply elasticity reduction in top 10% largest locations

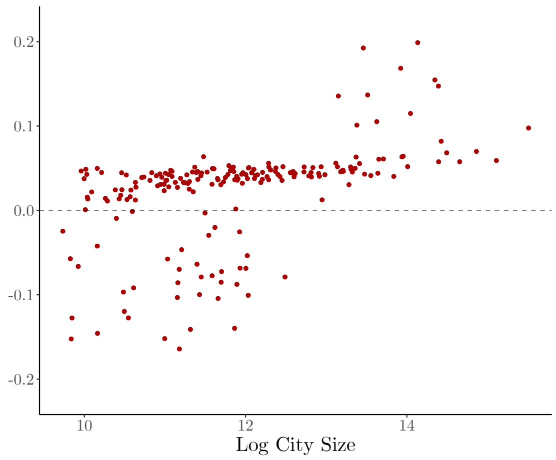
(a) Housing price changes



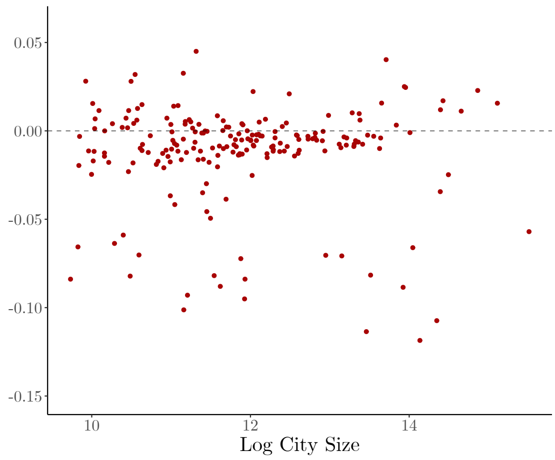
(b) Population changes



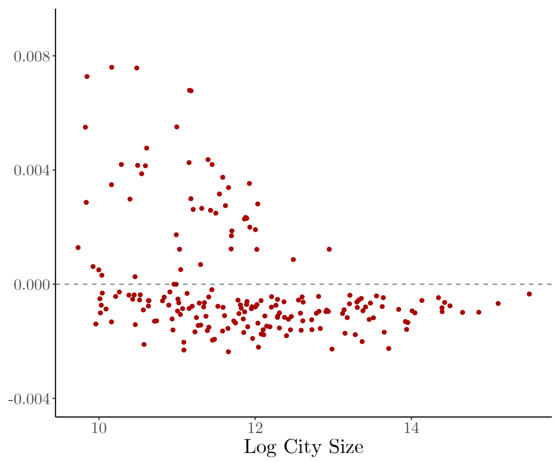
(c) Firm number changes



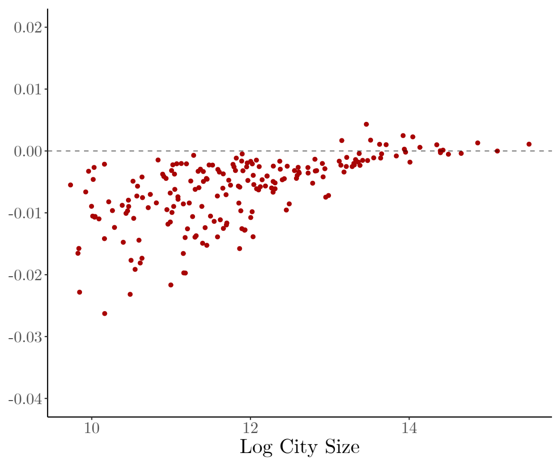
(d) Labor supply elasticity changes



(e) Markdown differences



(f) Wage changes



are standard in the quantitative spatial literature (Giannone et al. 2023), and Chetty, Hendren and Katz (2016) provide empirical evidence from the Moving to Opportunity experiment.

We consider a policy that pays a subsidy equivalent to 30% of average income to workers who move to the 10% largest locations. Results are shown in Figure 5 and in columns 3 and 4 of Table 5. Labor reallocation is substantial, comparable in magnitude to the housing supply policy. Population increases markedly in large cities and decreases in small ones (Figure 5b). Unlike the housing policy, however, housing prices rise on average by 1.1%, driven by higher demand in supply-constrained large locations. These increases are sizable in large cities (Figure 5a), while prices tend to fall in smaller cities experiencing out-migration.

Turning to the margins relevant for labor market power, we find large firm entry in big cities and firm exit in smaller ones (Figure 5c), following productivity changes linked to agglomeration economies as population relocates. Labor supply elasticities respond strongly in large cities: they rise substantially because both in-migration and out-migration increase. The subsidy not only draws workers into large cities but also makes it cheaper for current residents to move elsewhere, amplifying both margins (Figure 5d). In contrast, effects on small cities are theoretically ambiguous: out-migration increases (raising elasticity), while in-migration decreases (lowering elasticity).

These changes translate into sizable effects on markdowns. In large cities, markdowns fall by roughly 0.004, a substantial decline (-16%) given an average baseline markdown of 0.026, while the effects in small cities are mixed (Figure 5e). Wage changes mirror markdown patterns (Figure 5f): wages increase in large cities and decline in small ones.

Because the migration subsidy significantly alters labor market power, results differ meaningfully between the model with and without monopsony. Without labor market power, wage responses across locations are notably smaller (Appendix Figure D7c). Wages still rise in large cities due to productivity gains from agglomeration and complementarity between skill groups, but the absence of markdown adjustments mutes the overall effect. Similarly, average housing price increases are smaller in a model without labor market power (Table 5).

As a result, welfare implications differ meaningfully across the two environments. While the magnitudes are small in both cases, welfare turns slightly negative in the model with monopsony (-0.012%) and slightly positive in the model without monopsony (0.015%), mainly because housing prices rise less when labor market power is absent. Thus, even for a policy with relatively modest aggregate effects, modeling labor market power can alter the welfare evaluation. In both versions of the model, financing the subsidy requires increasing labor income taxes by about 0.42 percentage points.

Subsidy to Promote Firm Entry A third policy we examine is a subsidy targeted at firm entry. Unlike housing supply reforms or migration vouchers, which primarily operate through individual location decisions, this policy directly affects firm behavior. By lowering entry costs, the subsidy increases the number of potential competitors in selected labor markets, thereby reducing markdowns by increasing competition in the labor market. The subsidy is directed at labor markets located in the bottom 50% of the city-size distribution (110 lo-

Figure 5: Effect of subsidy (30% of average income) to migrate to top 10% largest locations

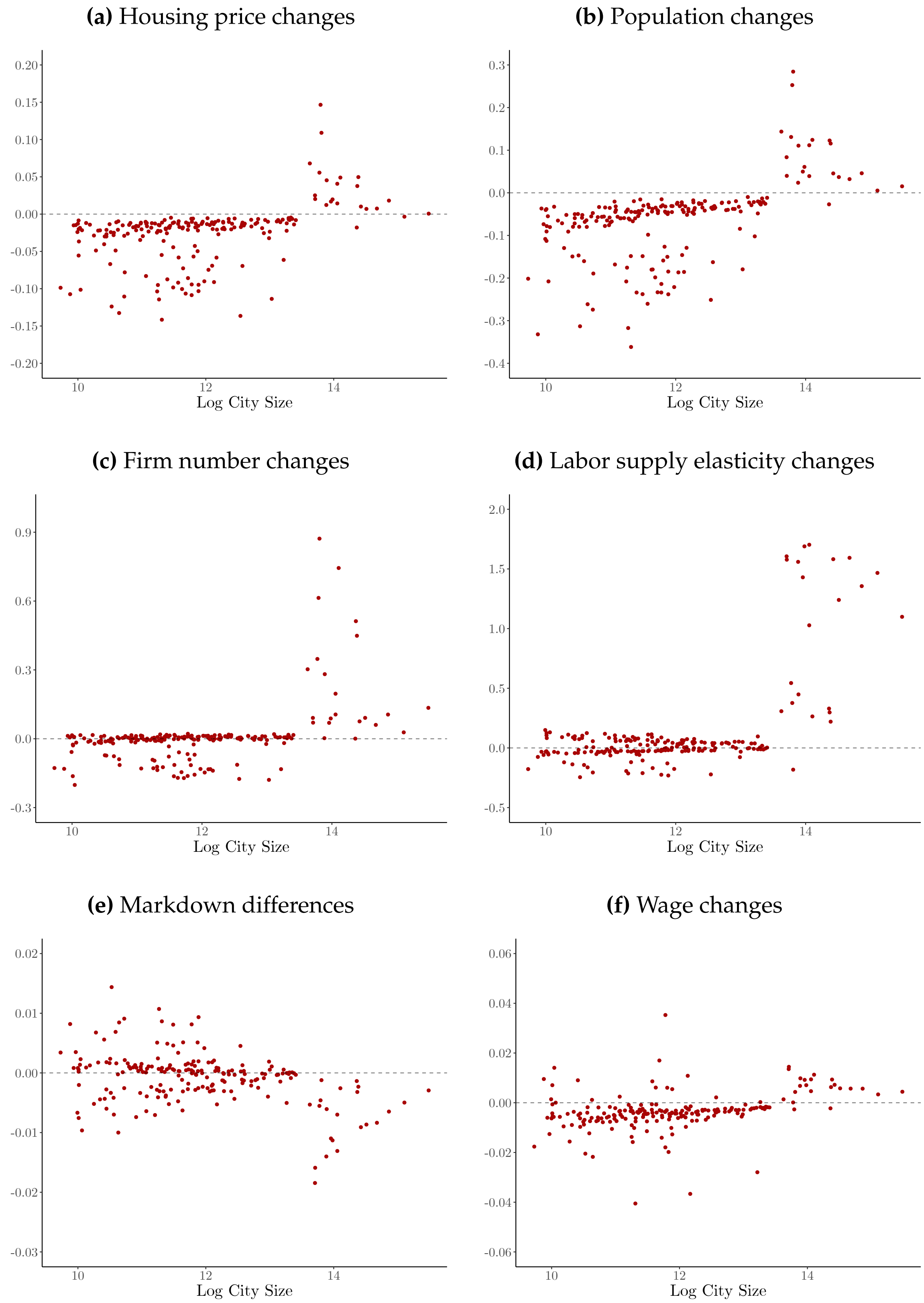
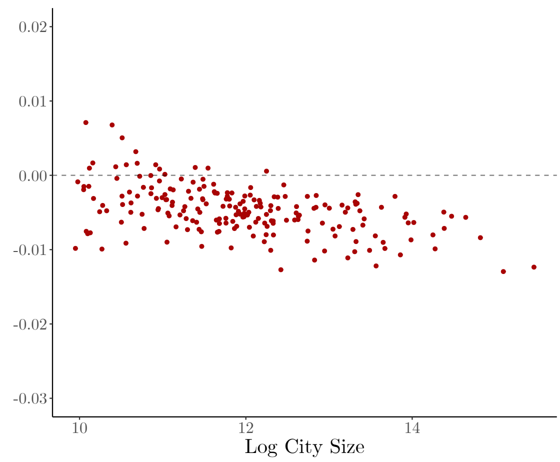
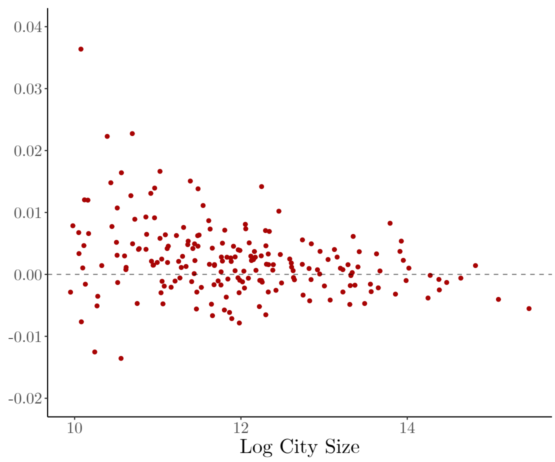


Figure 6: Firm entry subsidy (30× average income) in concentrated markets (DOJ-FTC threshold) in the bottom 50% cities

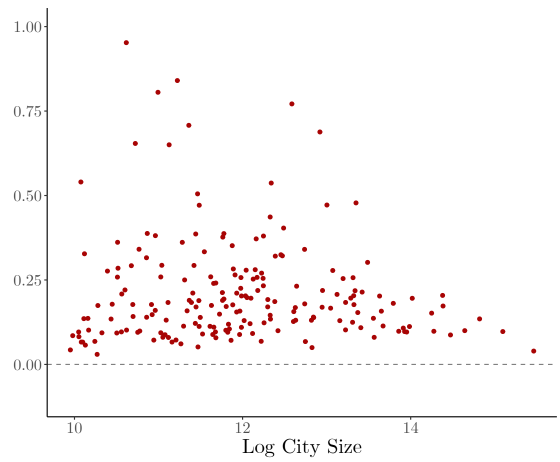
(a) Housing price changes



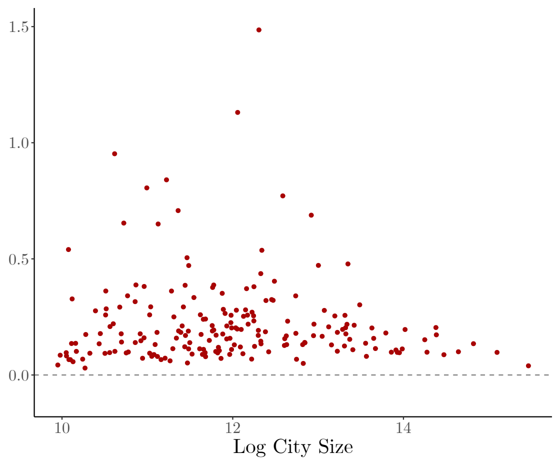
(b) Population changes



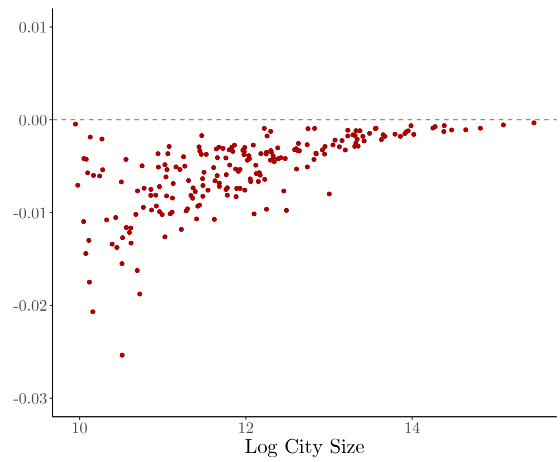
(c) Firm number changes



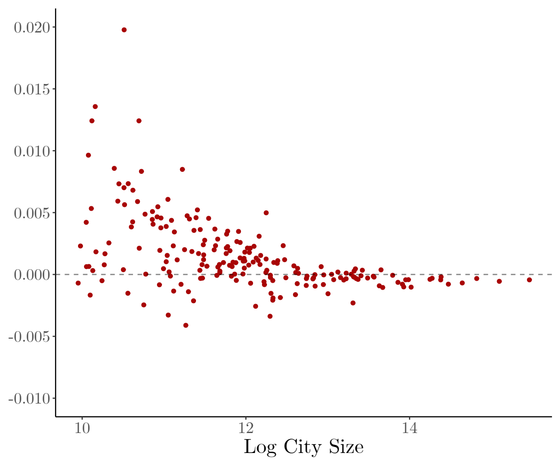
(d) Labor supply elasticity changes



(e) Markdown differences



(f) Wage changes



cations), and only in those local labor markets that are concentrated according above a HHI threshold of 0.20. We set the threshold at 0.20 because it lies midway between the Department of Justice and Federal Trade Commission horizontal merger guideline cutoffs: HHI above 0.15 denotes a "moderately concentrated" market, while HHI above 0.25 denotes a "highly concentrated" one (Azar, Marinescu and Steinbaum 2022). We implement this policy only in the model with labor market power, since entry costs are zero under perfect competition.[16]

The responses across cities are shown in Figure 6, and column 5 of Table 5 reports the aggregate effects. Firm entry increases everywhere, with the largest changes occurring in the smaller cities where the subsidy is applied (Figure 6c). As a result, markdowns decline especially in these locations (Figure 6e), and wages increase correspondingly (Figure 6f).

Population and housing price responses, instead, are modest and heterogeneous (Figures 6b and 6a), and far smaller than those generated under either the housing supply policy or the migration subsidy. The welfare effect is positive but small (0.015%). Despite being a far less costly intervention, requiring only a 0.0148 p.p. increase in labor income taxes, the firm entry subsidy is quite effective at reducing labor market power: the average markdown reduction of 0.0023 p.p. is more than half of that achieved by the much more expensive migration subsidy.

7 Conclusion

When is it important to model local labor market power in quantitative spatial frameworks, and when can it be safely abstracted from? We address this question by developing and estimating a spatial equilibrium model in which wage markdowns arise from migration frictions, industry-switching frictions, and imperfect competition among firms. Using four decades of U.S. data and a novel shift–share instrument based on trade shocks from Canada and Mexico, we recover micro-founded labor supply elasticities and decompose the evolution of local monopsony power across U.S. labor markets.

Our first set of results documents that local wage markdowns have declined substantially since 1980, roughly halving over the period, despite falling spatial mobility. The model attributes this decline primarily to two forces: rising switching of workers across industries, which translates into a more elastic labor supply, and increased firm entry, which reduces employer concentration. These channels jointly account for roughly 70% of the observed decline in markdowns, while changes in migration costs play only a minor role. This pattern is robust to alternative calibrations of the labor supply elasticity, indicating that the mechanisms behind the decline in monopsony power are not an artifact of a particular parameter choice.

We then use the model to evaluate three spatial policies. Relaxing housing supply constraints in large, productive cities generates sizable reallocation and non-trivial welfare gains, but has only muted effects on local labor market power. Labor supply elasticities move in off-

[16]The firm entry subsidy to each equivalent symmetric firms equals 30 times the average income in the economy.

setting ways across locations, so markdowns change little and aggregate outcomes are very similar to those of a standard competitive spatial model. By contrast, migration subsidies that encourage moves into high-productivity cities substantially increase labor supply elasticities in those markets and reduce local markdowns. Because this policy directly targets workers' outside options, the resulting wage and price responses differ across models with and without monopsony, and welfare effects change sign once labor market power is taken into account. Finally, a targeted firm entry subsidy in concentrated small markets produces relatively large markdown reductions at low fiscal cost, mainly by strengthening local competition among employers.

Taken together, these findings suggest that incorporating labor market power into spatial models is not always necessary, an important point in a literature where the computational demands of high-dimensional environments can be quite constraining. For policies that primarily operate through housing markets and generate only modest changes in labor supply elasticities or firm concentration, competitive frameworks appear to deliver reliable aggregate predictions. However, for policies that directly affect workers' mobility or the structure of local labor demand, such as migration subsidies, modeling the monopsony margin becomes essential for capturing price and welfare effects.

References

Adelman, Morris A. 1969. "Comment on the "H" Concentration Measure as a Numbers-Equivalent." *The Review of Economics and Statistics*, 99–101. 5, 11, 42

Ahlfeldt, Gabriel M, Duncan Roth, and Tobias Seidel. 2022. "Optimal Minimum Wages." *CEPR Discussion Paper No. DP16913*. 3

Autor, David H, and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review*, 103(5): 1553–1597. 12, 42

Azar, José A, Steven T Berry, and Ioana Marinescu. 2022. "Estimating Labor Market Power." *Working Paper*. 4

Azar, José, Ioana Marinescu, and Marshall Steinbaum. 2022. "Labor Market Concentration." *Journal of Human Resources*, 57(S): S167–S199. 4, 28

Azar, José, Ioana Marinescu, Marshall Steinbaum, and Bledi Taska. 2020. "Concentration in US Labor Markets: Evidence From Online Vacancy Data." *Labour Economics*, 66: 101886. 4

Bagga, Sadhika. 2023. "Firm Market Power, Worker Mobility, and Wages in the US Labor Market." *Journal of Labor Economics*, 41(S1): S205–S256. 3

Bamford, Iain. 2021. "Monopsony Power, Spatial Equilibrium, and Minimum Wages." *Working Paper*. 3

Bayer, Patrick, Fernando Ferreira, and Robert McMillan. 2007. "A Unified Framework for Measuring Preferences for Schools and Neighborhoods." *Journal of Political Economy*, 115(4): 588–638. 37

Bayer, Patrick, Nathaniel Keohane, and Christopher Timmins. 2009. "Migration and Hedonic Valuation: The Case of Air Quality." *Journal of Environmental Economics and Management*, 58(1): 1–14. 2, 10, 13, 14

Berger, David, Kyle Herkenhoff, Andreas R Kostøl, and Simon Mongey. 2024. "An Anatomy of Monopsony: Search Frictions, Amenities, and Bargaining in Concentrated Markets." *NBER Macroeconomics Annual*, 38(1): 1–47. 4

Berger, David, Kyle Herkenhoff, and Simon Mongey. 2022. "Labor Market Power." *American Economic Review*, 112(4): 1147–1193. 4

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica*, 63(4): 841–890. 2, 4, 10, 13

Bishop, Kelly C, Nicolai V Kuminoff, Sophie M Mathes, and Alvin D Murphy. 2024. "The Marginal Cost of Mortality Risk Reduction: Evidence From Housing Markets." *Journal of Urban Economics*, 139: 103627. 37

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2024. "Quasi-Experimental Shift-Share Research Designs." *The Review of Economic Studies*, 89(1): 181–213. 16, 17, 18, 46, 47

Bénabou, Roland. 2002. "Tax and Education Policy in a Heterogeneous-Agent Economy: What Levels of Redistribution Maximize Growth and Efficiency?" *Econometrica*, 70(2): 481–517. 9

Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro. 2019. "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock." *Econometrica*, 87(3): 741–835. 3

Card, David. 2009. "Immigration and Inequality." *American Economic Review*, 99(2): 1–21. 18, 19, 39

Card, David. 2022. "Who Set Your Wage?" *American Economic Review*, 112(4): 1075–1090. 4

Chetty, Raj, Nathaniel Hendren, and Lawrence F Katz. 2016. "The Effects of Exposure to Better Neighborhoods on Children: New Evidence From the Moving to Opportunity Experiment." *American Economic Review*, 106(4): 855–902. 25

Datta, Nikhil. 2024. "Local Monopsony Power." *Working Paper*. 3, 4

Davidoff, Thomas. 2016. "Supply Constraints Are Not Valid Instrumental Variables for Home Prices Because They Are Correlated With Many Demand Factors." *Critical Finance Review*, 5(2): 177–206. 16

Deb, Shubhdeep, Jan Eeckhout, Aseem Patel, and Lawrence Warren. 2022. "What Drives Wage Stagnation: Monopsony or Monopoly?" *Journal of the European Economic Association*, 20(6): 2181–2225. 4

Diamond, Rebecca. 2016. "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000." *American Economic Review*, 106(3): 479–524. 4, 17, 38

Duranton, Gilles, and Diego Puga. 2004. "Micro-Foundations of Urban Agglomeration Economies." In *Handbook of Regional and Urban Economics*. Vol. 4, 2063–2117. Elsevier. 9

Duranton, Gilles, and Matthew A Turner. 2011. "The Fundamental Law of Road Congestion: Evidence From US Cities." *American Economic Review*, 101(6): 2616–52. 38

Ganong, Peter, and Daniel Shoag. 2017. "Why Has Regional Income Convergence in the US Declined?" *Journal of Urban Economics*, 102: 76–90. 4

Gaubert, Cecile, Patrick Kline, Damian Vergara, and Danny Yagan. 2025. "Place-Based Redistribution." *American Economic Review*, 115(10): 3415–3450. 4

Giannone, Elisa, Qi Li, Nuno Paixao, and Xinle Pang. 2023. "Unpacking Moving." *Working Paper*. 4, 25

Glaeser, Edward L, and Joseph Gyourko. 2002. "The Impact of Zoning on Housing Affordability." *National Bureau of Economic Research Cambridge, Mass., USA*. 3, 22

Guner, Nezih, Remzi Kaygusuz, and Gustavo Ventura. 2014. "Income Taxation of US Households: Facts and Parametric Estimates." *Review of Economic Dynamics*, 17(4): 559–581. 9, 18, 19

Hsieh, Chang-Tai, and Enrico Moretti. 2019. "Housing Constraints and Spatial Misallocation." *American Economic Journal: Macroeconomics*, 11(2): 1–39. 4

Jia, Ning, Raven Molloy, Christopher Smith, and Abigail Wozniak. 2023. "The Economics of Internal Migration: Advances and Policy Questions." *Journal of Economic Literature*, 61(1): 144–180. 6

Kaas, Leo, Georgi Kocharkov, Edgar Preugschat, and Nawid Siassi. 2021. "Low Homeownership in Germany—A Quantitative Exploration." *Journal of the European Economic Association*, 19(1): 128–164. 10

Kline, Patrick, and Enrico Moretti. 2014. "People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs." *Annual Review of Economics*, 6(1): 629–662. 4

Lutz, Chandler, and Ben Sand. 2023. "Highly Disaggregated Land Unavailability." *Working Paper*. 12

Manning, Alan. 2021. "Monopsony in Labor Markets: A Review." *ILR Review*, 74(1): 3–26. 4

Mathes, Sophie M. 2025. "The Dynamics Of Residential Sorting And Health: Implications Of Climate Change In The United States." *International Economic Review*, 66(2): 711–756. 14

Melo, Patricia C, Daniel J Graham, and Robert B Noland. 2009. "A Meta-Analysis of Estimates of Urban Agglomeration Economies." *Regional Science and Urban Economics*, 39(3): 332–342. 19

Rinz, Kevin, et al. 2018. "Labor Market Concentration, Earnings Inequality, and Earnings Mobility." *Center for Administrative Records Research and Applications Working Paper*, 10. 4

Saiz, Albert. 2010. "The Geographic Determinants of Housing Supply." *The Quarterly Journal of Economics*, 125(3): 1253–1296. 9, 12, 18, 19, 39, 44

Schott, Peter K. 2008. "The Relative Sophistication of Chinese Exports." *Economic Policy*, 23(53): 6–49. 15, 38

Sokolova, Anna, and Todd Sorensen. 2021. "Monopsony in Labor Markets: A Meta-Analysis." *ILR Review*, 74(1): 27–55. 4, 19, 20

Vial Lecaros, Felipe, Román D Zárate, and Jorge Pérez Pérez. 2023. "Urban Transit Infrastructure: Spatial Mismatch and Labor Market Power." *Working Paper*. 4

Yeh, Chen, Claudia Macaluso, and Brad Hershbein. 2022. "Monopsony in the US labor market." *American Economic Review*, 112(7): 2099–2138. 4

Appendix

This Appendix is organized as follows. Section A provides details about the model. Section B presents further details on the estimation strategy. Section C provides additional information on the policy counterfactuals. Finally, Section D contains additional tables and figures referenced in the text.

A Model

A.1 Labor Supply Derivative

The labor supply curve is for labor of educational type e is given by aggregating the choice probabilities across all individuals i of type e.

$$\begin{aligned} N^e_{j'k't} &= \sum_{i=1}^{N^e} p^e_{ij'k't}(j,k) \qquad (22) \\ &= \sum_{i=1}^{N^e} \frac{\exp\left(\beta_w \log(w^e_{j'k't}) + \beta_r \log(r_{j't}) + \xi^e_{j'k't} - \mu^e_t(j(i),j') - \delta^e_t(k(i),k')\right)}{\sum\limits_{j'',k''} \exp\left(\beta_w \log(w^e_{j''k''t}) + \beta_r \log(r_{j''t}) + \xi^e_{j''k''t} - \mu^e_t(j(i),j'') - \delta^e_t(k(i),k'')\right)} \end{aligned}$$

Denote as a shorthand

$$\begin{aligned} f^e_{ij'k't} &\equiv \exp\left(\beta_w \log(w^e_{j'k't}) + \beta_r \log(r_{j't}) + \xi^e_{j'k't} - \mu^e_t(j(i),j') - \delta^e_t(k(i),k')\right) \\ \Rightarrow N^e_{j'k't} &= \sum_{i=1}^{N^e} \frac{f^e_{ij'k't}}{\sum\limits_{j''k''} f^e_{ij''k''t}} \end{aligned}$$

Consider the labor supply $N^e_{j'k't}$ in location-industry $j'k'$ as a function of its own wage $w_{j'k't}$. The own wage $w^e_{j'k't}$ appears in the numerator and denominator of every individual-level summand of equation (22). Within each individual-level summand, $w^e_{j'k't}$ is part of only one summand in the denominator. Therefore, the derivative of the denominator with respect to $w_{j'k't}$ is the same as the derivative of the numerator.

$$\begin{aligned} \frac{\partial N^e_{j'k't}}{\partial w^e_{j'k't}} &= \sum_{i=1}^{N^e} \frac{f^e_{ij'k't}\frac{\beta_w}{w^e_{ij'k't}}(\sum_{j''k''} f^e_{ij''k''t}) - f^e_{ij'k't} f^e_{ij'k't}\frac{\beta_w}{w^e_{ij'k't}}}{(\sum\limits_{j''k''} f^e_{ij''k''t})^2} \\ &= \frac{\beta_w}{w^e_{ij'k't}} \left(\sum_{i=1}^{N^e} \frac{f^e_{ij'k't}(\sum_{j'} f^e_{ij'k't})}{(\sum\limits_{j''k''} f^e_{ij''k''t})^2} - \sum_{i=1}^{N^e} \frac{f^e_{ij'k't} f^e_{ij'k't}}{(\sum\limits_{j''k''} f^e_{ij''k''t})^2} \right) \\ &= \frac{\beta_w}{w^e_{ij'k't}} \left(\sum_{i=1}^{N^e} \frac{f^e_{ij'k't}}{(\sum\limits_{j''k''} f^e_{ij''k''t})} - \sum_{i=1}^{N^e} \frac{f^e_{ij'k't} f^e_{ij'k't}}{(\sum\limits_{j''k''} f^e_{ij''k''t})^2} \right) \end{aligned}$$

$$
\begin{aligned}
&= \frac{\beta_w}{w^e_{ij'k't}} \left(\sum_{i=1}^{N^e} p_{ij'k't} - \sum_{i=1}^{N^e} p^2_{ij'k't} \right) \\
&= \frac{\beta_w}{w^e_{ij'k't}} \left(\sum_{i=1}^{N^e} \left(p_{ij'k't} - p^2_{ij'k't} \right) \right)
\end{aligned}
$$

or

$$
\frac{\partial N^e_{j'k't}}{\partial w^e_{j'k't}} = \frac{\beta_w}{w^e_{ij'k't}} \left(\sum_{i=1}^{N^e} p_{ij'k't}(1 - p_{ij'k't}) \right) \tag{23}
$$

A.2 Labor Supply Derivative Including Impacts on Local Rents

If we assume that firms take into account that wages $w^e_{j'k't}$ may affect local rents $r_{j't}$, we obtain the following expression for the labor supply elasticity as considered by strategic firms:

$$
\frac{\partial N^e_{j'k't}}{\partial w^e_{j'k't}} = \left(\frac{\beta_w}{w^e_{ij'k't}} + \frac{\beta_r}{r_{j't}} \cdot \frac{\partial r_{j't}}{\partial w_{j'k't}} \right) \left(\sum_{i=1}^{N^e} p_{ij'k't}(1 - p_{ij'k't}) \right) \tag{24}
$$

Counterfactual exercises that use equation (24) instead of the baseline expression in (6) show that incorporating the effect of wages on rents has only a small impact on the implied labor supply elasticities. Intuitively, this reflects the fact that a change in wages in a single location–industry market (one of 177 industries within a location) has only a limited effect on overall citywide housing demand, and thus on equilibrium housing prices.

A.3 Equilibrium

An equilibrium is a distribution of workers $(N^n_{j'k't}, N^c_{j'k't})$ across location-industries, wages $(w^n_{j'k't}, w^c_{j'k't})$, rents $r_{j't}$, and labor income tax level τ_0 such that

1. Local labor markets clear for both types of labor,

$$
\begin{aligned}
N^n_{j'k't} = m_{j'k't} n^n &= \sum_i p^n_{ij'k't} \\
N^c_{j'k't} = m_{j'k't} n^c &= \sum_i p^c_{ij'k't}
\end{aligned}
$$

2. Firms' labor demand $(n^n_{j'k't}, n^c_{j'k't})$ is an equilibrium of the augmented Cournot game within each local labor market, where each firm chooses demand for each type of labor to maximize their profits, taking as given the demand of all other firms and labor supply elasticities:

$$
A_{j'k't} \left(\theta^c_{j'k't} (n^c)^{\frac{\rho-1}{\rho}} + \theta^n_{j'k't} (n^n)^{\frac{\rho-1}{\rho}} \right)^{\frac{1}{\rho-1}} \theta^e_{j'k't} (n^e)^{-\frac{1}{\rho}} - \left. \frac{\partial w^e_{j'k't}}{\partial n^e} \right|_{N^e_{j'k't}} n^e - w^e_{j'k't} \;=\; 0
$$

Firms satisfy the free entry condition $\pi^*_{j'k't} = F_{j'k't}$.

3. Housing market supply $h^S_{j't}$ equals demand $h^D_{j't}$ in each location j' and year t:

$$\begin{aligned} h^S_{j't} &= \left(\frac{r_{j't}}{\kappa_{j't}}\right)^{\frac{1}{\gamma_{j't}}} \\ &= \sum_{k''} N^c_{j'k''t} \frac{(-\beta_r) w^c_{j'k''t}}{\beta_w r_{j't}} + \sum_{k''} N^n_{j'k''t} \frac{(-\beta_r) w^n_{j'k''t}}{\beta_w r_{j't}} \\ &= h^D_{j't} \end{aligned}$$

4. Workers' choices of locations and industries solve their utility maximization problems described in equation (1).

5. The level of taxes τ_0 balances the Government budget, i.e.,

$$T_t = \overline{G}_t + G^p_t,$$

where tax revenues are given by

$$T_t = \sum_{j''} \sum_{k''} N^c_{j''k''t} w^c_{j''k''t} \left(1 - \varsigma_0 \left(\frac{w^c_{j''k''t}}{\overline{w}_t}\right)^{-\varsigma_1}\right) + \sum_{j''} \sum_{k''} N^n_{j''k''t} w^n_{j''k''t} \left(1 - \varsigma_0 \left(\frac{w^n_{j''k''t}}{\overline{w}_t}\right)^{-\varsigma_1}\right),$$

$\overline{G}_t$ denotes expenditure on public goods, and G^p_t denotes expenditure on policies.

B Estimation

B.1 Data

Locations Metropolitan areas are observed in the Census data for individuals who reside in PUMAs that are entirely contained in delineated metro areas. Most metro areas are fully and correctly identified as a collection of PUMAs. The Census data does not identify the metro area for PUMAs that straddle metro areas, located typically on the outskirts. In this case, we do not consider the residents to be residents of the metro area.[17] Metro areas in which a nontrivial share of residents are misidentified as non-residents are mostly Puerto Rican metro areas, which we do not consider in this study, and a few metro areas in geographically small east coast states, e.g. Worcester MA, Waterbury CT, New-Haven Meriden CT, and Nashua NH.

Market Level Wages To measure location-industry specific wages $\log(w_{jkt})$, we regress individual annual after-tax wages on demographics and location-by-industry fixed effects, separately for each educational group and year t:

$$\log(w^e_{ijkt}) = \beta^e_{1t}\text{age}_{it} + \beta^e_{2t}\text{gender}_{it} + \beta^e_{3t}\text{race}_{it} + \alpha_{j(i)k(i)} + \varepsilon_{it} \tag{25}$$

We measure age in bins (below 30, 30-40, 40-50, 50-60, 60+) to account for non-linearities in wages by age. Therefore, in a slight abuse of notation, age_{it} stands for a set of count variables and β_{1t} stands for a set of four coefficients, with 30-40 being the omitted reference group. We define the market-level wage index $\log(w_{jkt})$ for each period t as the location fixed effect α_{jkt} obtained from this regression.

Location and Industry-Level Wages The estimation of location-specific wages, $\log(w_{jt})$, follows the same approach as in equation (25), with the addition of industry fixed effects to account for differences in industry composition across locations:

$$\log(w^e_{ijt}) = \beta^e_{1t}\text{age}it + \beta^e_{2t}\text{gender}it + \beta^e_{3t}\text{race}it + \alpha_{j(i)} + \alpha_{k(i)} + \varepsilon_{it} \tag{26}$$

In this specification, $\alpha_{j(i)}$ captures the location-level wage component, controlling for observable worker characteristics and industry composition. Similarly, $\alpha_{k(i)}$ captures the industry-level wage component, obtained while controlling for location fixed effects.

Housing Rents Analogously to wages, we calculate a rental index for each location j and year t in the sample to facilitate comparisons of the annual cost of housing across locations. We follow Bayer, Ferreira and McMillan (2007) and Bishop et al. (2024) by pooling data on rents and property values. As the dependent variable, we use annual gross rent for renters

[17] The percentage of the population by metro area that is misidentified can be found here: https://usa.ipums.org/usa/volii/incompmetareas.shtml.

and property value for home owners. We estimate separately for each year:

$$\log(p_{ijt}) = \beta_{1t}\mathbf{x}_{it} + \beta_{2t}\text{own}_{it} + \sum_s \beta_{3st}\,\text{own}_{it} \cdot I_{st} + \alpha_{j(i)t} + \varepsilon_{it} \tag{27}$$

$\mathbf{x}_{it}$ is a vector of housing characteristics including the number of bedrooms, the age of the structure, and the type of unit. The indicator own_{it} controls for owner-occupancy. We allow the ratio of home values to annual gross rents to vary by state by adding a set of state indicator variables I_{st} interacted with the ownership indicator. We define the market-level rent index $\log(r_{jt})$ as the location fixed effect α_{jt}.

Local Amenities Observable amenities are included as controls in the estimation of labor supply parameters in Section 4.3. We measure amenities at the location–year level following Diamond (2016). Information on amenities related to retail, transportation, innovation, crime, environmental quality, and schooling quality is drawn from multiple sources, including the U.S. Census, the County Business Patterns, the FBI Uniform Crime Reports, the EPA Air Quality Monitoring System, the Census of Governments, the NBER Patent Database, the U.S. Patent and Trademark Office, and Duranton and Turner (2011). Retail amenities capture the variety of shops and entertainment options in each city, measured by the per capita number of clothing stores, eating and drinking places, and cinemas. Transportation amenities reflect the quality of public transit and road infrastructure, including indicators such as buses per person, an overall public transit rating, and average daily traffic on major roads. Innovation activity is proxied by the number of patents per capita. Crime data include both violent and property crimes per person. Environmental quality is measured by per capita government spending on parks and recreation and by the EPA air quality index. School quality indicators include per-student government spending on K–12 education and the ratio of students enrolled in private to public schools.

A composite amenity index is then constructed for each location and year using principal component analysis (PCA), following Diamond (2016). Unlike Diamond, we extend the index to 2019. Because transportation data are unavailable for that year, we use 2010 values as proxies for transportation amenities.

Trade Data Industry-level import data used for the shift–share IV are drawn from Schott (2008), who compiled detailed trade information from the U.S. Census Bureau.

B.2 Housing and Labor Markets

Housing Market To estimate the remaining housing supply parameters, we substitute the model-based expressions for housing demand (equation 12) into the inverse housing supply functions (equation 13) and solve for $\log(r_{jt})$:

$$\begin{aligned}
\log(r_{jt}) &= \log(\kappa_{jt}) + \gamma_{jt}\log\left(\sum_k N^n_{jkt}\frac{-\beta_r w^n_{jkt}}{\beta_w r_{jt}} + \sum_k N^c_{jkt}\frac{-\beta_r w^c_{jkt}}{\beta_w r_{jt}}\right) \\
&= \log(\kappa_{jt}) + \gamma_{jt}\log\left(\left(\sum_k N^n_{jkt}\frac{-\beta_r w^n_{jkt}}{\beta_w} + \sum_k N^c_{jkt}\frac{-\beta_r w^c_{jkt}}{\beta_w}\right)\frac{1}{r_{jt}}\right) \\
&= \log(\kappa_{jt}) + \gamma_{jt}\log\left(\sum_k N^n_{jkt}\frac{-\beta_r w^n_{jkt}}{\beta_w} + \sum_k N^c_{jkt}\frac{-\beta_r w^c_{jkt}}{\beta_w}\right) - \gamma_{jt}\log(r_{jt}) \\
(1+\gamma_{jt})\log(r_{jt}) &= \log(\kappa_{jt}) + \gamma_{jt}\log\left(\sum_k N^n_{jkt}\frac{-\beta_r w^n_{jkt}}{\beta_w} + \sum_k N^c_{jkt}\frac{-\beta_r w^c_{jkt}}{\beta_w}\right)
\end{aligned}$$

$$\log(r_{jt}) = \underbrace{\frac{\log(\kappa_{jt})}{(1+\gamma_{jt})}}_{\equiv k_{jt}} + \frac{\gamma_{jt}}{(1+\gamma_{jt})}\log\left(\sum_k N^n_{jkt}\frac{-\beta_r w^n_{jkt}}{\beta_w} + \sum_k N^c_{jkt}\frac{-\beta_r w^c_{jkt}}{\beta_w}\right) \tag{28}$$

Using the market-level rents and wages (equations 25 and 27), inverse housing supply elasticities γ_{jt} from Saiz (2010), and our estimates of β_w and β_r as described in Section 4, we then choose k_{jt} to equate the left and right-hand sides of equation (28).

Labor Market The parameters of interest on the labor demand side are total factor productivity A_{jkt} and factor shares θ^c_{jkt} and θ^n_{jkt}, the parameters of the production function. For each year and location-industry, we estimate these using the strategic first-order conditions:

$$\begin{aligned}
\frac{\partial\, \pi_{jkt}}{\partial\, n^n} &= A_{jkt}\left(\theta^c_{jkt}(n^c)^{\frac{\rho-1}{\rho}} + \theta^n_{jkt}(n^n)^{\frac{\rho-1}{\rho}}\right)^{\frac{1}{\rho-1}}\theta^n_{jkt}\,(n^n)^{-\frac{1}{\rho}} - \left.\frac{\partial w^n_{jkt}}{\partial n^n}\right|_{N^n_{jkt}} n^n - w^n_{jkt} \\
&\stackrel{!}{=} 0 \qquad\qquad (29) \\
\frac{\partial\, \pi_{jkt}}{\partial\, n^c} &= A_{jkt}\left(\theta^c_{jkt}(n^c)^{\frac{\rho-1}{\rho}} + \theta^n_{jkt}(n^n)^{\frac{\rho-1}{\rho}}\right)^{\frac{1}{\rho-1}}\theta^c_{jkt}\,(n^c)^{-\frac{1}{\rho}} - \left.\frac{\partial w^c_{jkt}}{\partial n^c}\right|_{N^c_{jkt}} n^c - w^c_{jkt} \\
&\stackrel{!}{=} 0 \qquad\qquad (30)
\end{aligned}$$

Combining the two conditions and rearranging yields

$$\frac{\theta^n_{jkt}}{\theta^c_{jkt}} = \frac{\left.\frac{\partial w^n_{jkt}}{\partial n^n}\right|_{N^n_{jkt}} n^n + w^n_{jkt}}{\left.\frac{\partial w^c_{jkt}}{\partial n^c}\right|_{N^c_{jkt}} n^c + w^c_{jkt}}\left(\frac{n^n}{n^c}\right)^{\frac{1}{\rho}} \tag{31}$$

Location-industry specific wages and employment are taken from the data. We obtain microfounded local labor supply elasticities $\left.\frac{\partial w^n_{jkt}}{\partial n^n}\right|_{N^n_{jkt}}$ and $\left.\frac{\partial w^c_{jkt}}{\partial n^c}\right|_{N^c_{jkt}}$ directly from derivative of the labor supply functions in equation (5) using the inverse function theorem.[18] Following Card (2009), we set ρ to 2. Using the assumption $\theta^c_{jkt} + \theta^n_{jkt} = 1$, we now have estimates for factor shares θ^c_{jkt} and θ^n_{jkt} and can plug these into either equation (29) or (30) to recover A_{jkt}. In the

[18] See Appendix Section A.1 for derivations.

counterfactual exercises, we treat productivity and factor shares as exogenous and keep them fixed.

Wage markdowns With productivity and factor shares estimates in hand, we calculate counterfactual competitive wages as the market-clearing wages that would emerge if firms behaved as price-takers:

$$\hat{w}_{jkt}^{comp,n} = A_{jkt}\left(\theta_{jkt}^{c}(n^c)^{\frac{\rho-1}{\rho}} + \theta_{jkt}^{n}(n^n)^{\frac{\rho-1}{\rho}}\right)^{\frac{1}{\rho-1}}\theta_{jkt}^{n}\,(n^n)^{-\frac{1}{\rho}} - \underbrace{\left.\frac{\partial w_{jkt}^{n}}{\partial n^n}\right|_{N_{jkt}^{n}}}_{=0} n^n \tag{32}$$

$$\hat{w}_{jkt}^{comp,c} = A_{jkt}\left(\theta_{jkt}^{c}(n^c)^{\frac{\rho-1}{\rho}} + \theta_{jkt}^{n}(n^n)^{\frac{\rho-1}{\rho}}\right)^{\frac{1}{\rho-1}}\theta_{jkt}^{c}\,(n^c)^{-\frac{1}{\rho}} - \underbrace{\left.\frac{\partial w_{jkt}^{c}}{\partial n^c}\right|_{N_{jkt}^{c}}}_{=0} n^c \tag{33}$$

The resulting markdowns depend on the number of symmetric Cournot players in each market and on the inverse labor supply elasticities in each location-industry, which come from our structural model of labor supply. We calculate markdowns md_{jkt}^{e} using the ratio of the difference between observed wages w_{jkt}^{e} and competitive wages $\hat{w}_{jkt}^{comp,e}$:

$$md_{jkt}^{e} = 1 - \frac{w_{jkt}^{e}}{\hat{w}_{jkt}^{comp,e}} \tag{34}$$

C Policy Counterfactuals

C.1 Welfare Measure

Let the aggregate utility in the benchmark and in the policy counterfactual with consumption tax Δc be denoted by V and $\hat{V}(\Delta c)$, respectively. The consumption-equivalent tax Δc is defined such that

$$
\begin{aligned}
V - \hat{V}(\Delta c) = 0 \\
V &= \frac{1}{N}\sum_{i=1}^{N}\{u_i(c_i^*, h_i^*, j^*, k^*|j, k)\} \\
\hat{V}(\Delta c) &= \frac{1}{N}\sum_{i=1}^{N}\{u_i((\Delta c)c_i', h_i', j', k'|j, k)\}
\end{aligned}
$$

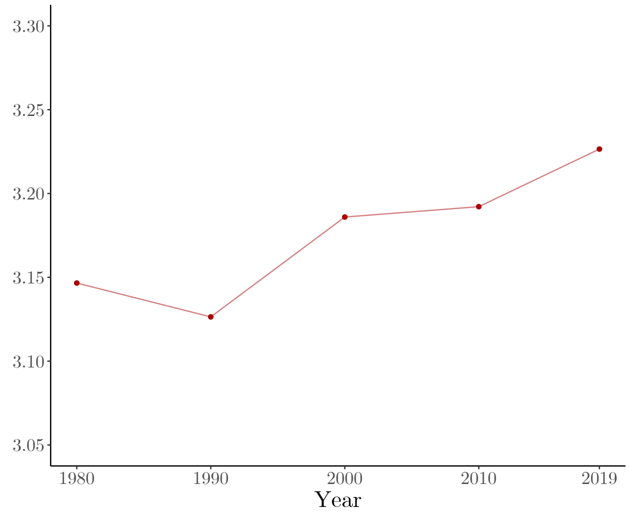
where (c_i^*, h_i^*, j^*, k^*) and (c_i', h_i', j', k') denote optimal choices in the benchmark and counterfactual equilibria, $u_i(\cdot)$ is the utility function defined in equation (1), and N is the number of simulated individuals.

The consumption tax parameter Δc adjusts all agents' consumption uniformly either upwards or downwards. A value of $\Delta c > 1$ suggests that, following the policy implementation, agents require a higher level of consumption to be indifferent with the benchmark. Conversely, $\Delta c < 1$ indicates that agents would give up part of their consumption to keep the policy.

Our measure of welfare is given $1 - \Delta c$. In other words, welfare measures the percentage change in consumption that the average worker would require, or give up, in order to be indifferent between the counterfactual and the benchmark. We don't analyze welfare along the transition path between steady-states. In particular, we compare workers who are either in the benchmark equilibrium or in the counterfactual equilibrium after prices, wages, and taxes have already converged.

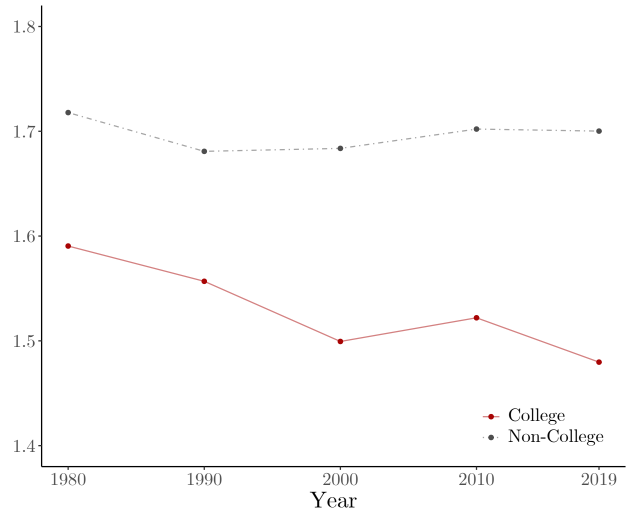
D Additional Figures and Tables

Figure D1: Symmetric establishments per market, log mean



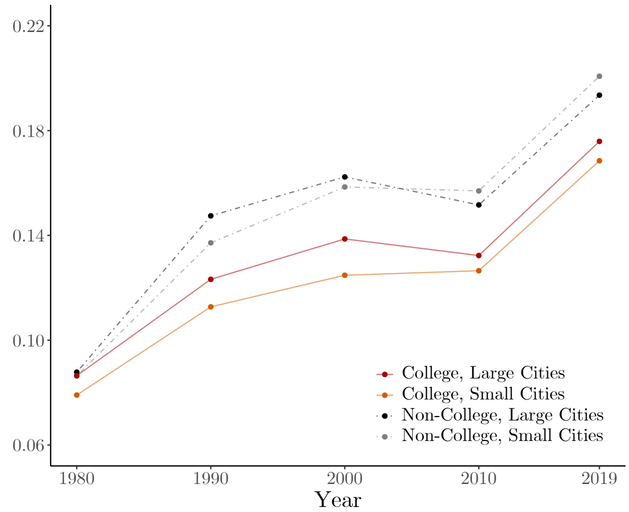
Notes: CPS Data (1980–2017). The plotted values represent the mean number of establishments across local labor markets. "Symmetric" establishments refer to the hypothetical number of equally-sized establishments that would yield the observed local employment concentration (Adelman 1969).

Figure D2: Mean task distance across industries



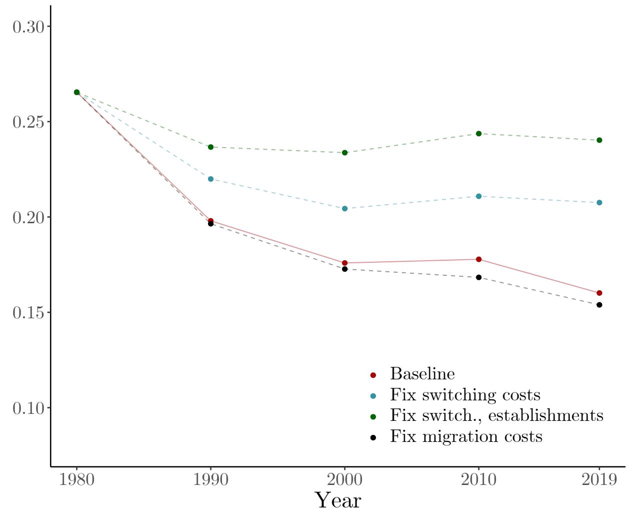
Notes: DOT 1977 Data, Autor and Dorn (2013).

Figure D3: Annual industry switching rate



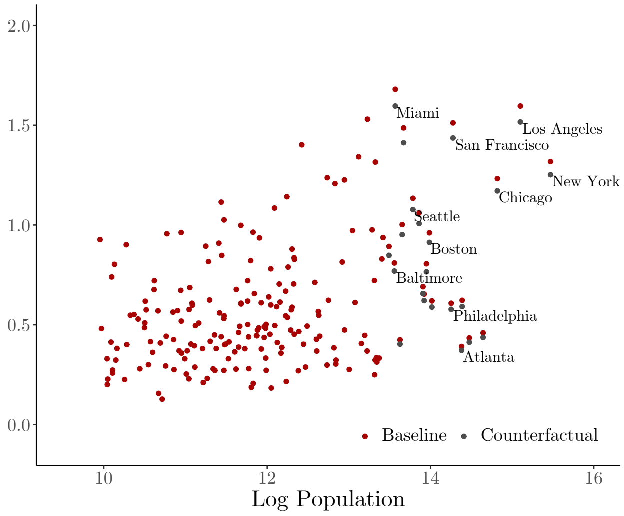
Notes: CPS Data (1980–2017).

Figure D4: Mean markdowns across location-industries



Notes: The figure plots average markdowns across local labor markets by decade, matching a median labor supply elasticity of 5 in 2019. The red line shows the baseline model, while dashed lines report counterfactual simulations fixing specific parameters to their 1980 values. See text for details.

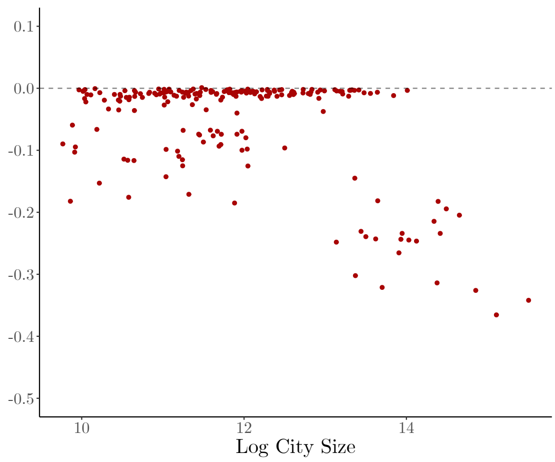
Figure D5: Inverse housing supply elasticity η^e_{jkt}, before and after the housing policy



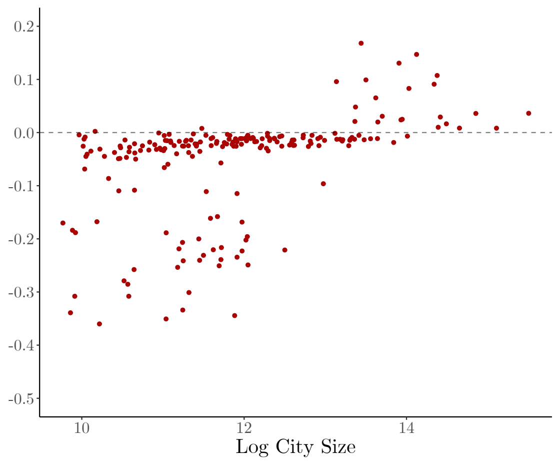
Notes: Housing supply elasticities from Saiz (2010). Counterfactual elasticities reduce by 5% the baseline elasticities in the 10% largest locations.

Figure D6: Effect of reducing by 5% inverse housing supply elasticity in top 10% largest locations, model without labor market power

(a) Housing price changes



(b) Population changes



(c) Wage changes

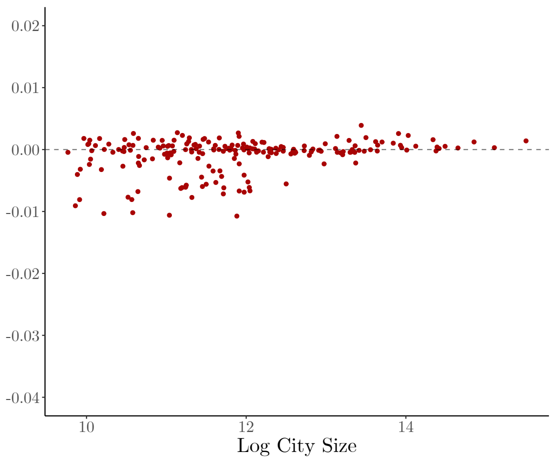
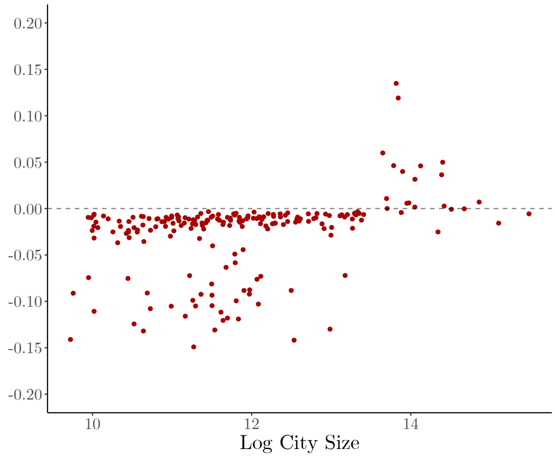
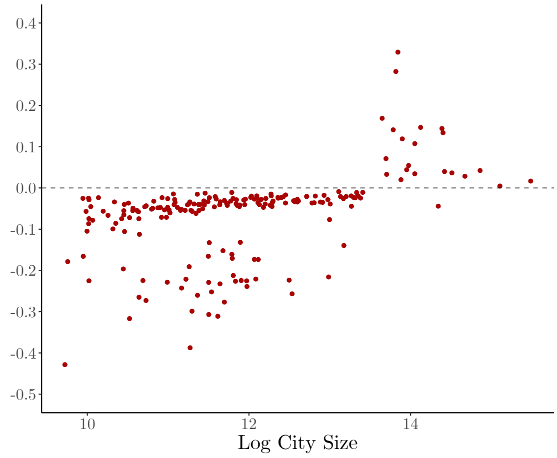


Figure D7: Effect of subsidy (30% of average income) to migrate to top 10% largest locations, model without labor market power

(a) Housing price changes



(b) Population changes



(c) Wage changes

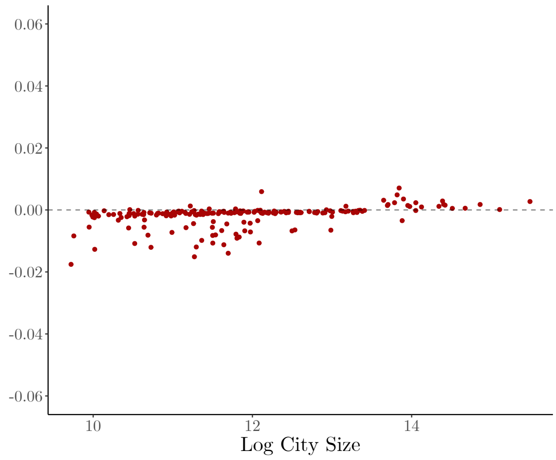


Table D1: Relationship between shifts and industry-level observables

	Δ Mean Age	Δ Male Share	Δ Black Share	Δ International Migration Share
	(1)	(2)	(3)	(4)
Δlog Imports	-0.0456	-0.0011	0.0003	0.0042**
	(0.0814)	(0.0022)	(0.0010)	(0.0021)
College FEs	✓	✓	✓	✓
Observations	128	128	128	128

Notes: All specifications include college fixed effects. Heteroskedasticity-robust standard errors in parentheses. **p*<0.1, ***p*<0.05, ****p*<0.01.

Table D2: OLS and IV estimates of labor supply parameters, placebo regression

		Δ Log Wage	Δ Log Rent
		(1)	(2)
Wage IV		0.2069***	0.3547***
		(0.0439)	(0.0836)
Rent IV (Housing Elasticity)		-0.1365	-0.1752
		(0.1023)	(0.2624)
Rent IV (Land Unavailability)		-0.0514	-0.4936
		(0.1661)	(0.4704)
Local Sum Shares Wage IV		-0.7927***	-1.555***
		(0.0940)	(0.1849)
Local Sum Shares Rent IV (Housing Elasticity)		0.6634***	0.8434
		(0.2138)	(0.5181)
Local Sum Shares Rent IV (Land Unavailability)		-0.0147	1.292
		(0.3473)	(0.9117)
Controls:	College FEs	✓	✓
	City Amenities	✓	✓
	International Migration	✓	✓
Observations		438	438
F-test		8.12	5.56

Notes: The table reports estimates of equation (21). Column (1) presents OLS estimates, while column (2) reports IV estimates. All specifications include college fixed effects, city amenities, the local sum of exposure shares, and changes in international migration at the industry level weighted by local exposure shares (Borusyak, Hull and Jaravel 2024). Heteroskedasticity-robust standard errors in parentheses. **p*<0.1, ***p*<0.05, ****p*<0.01.

Table D3: OLS and IV estimates of labor supply parameters, placebo regression

		Δ Mean Utility Locations	
		(1)	(2)
Δ Log Wage		-0.2343	-0.5671
		(0.3044)	(0.8657)
Δ Log Rent		0.1161	0.2613
		(0.1213)	(0.5496)
Controls:	College FEs	✓	✓
	City Amenities	✓	✓
	Local Sum of Shares		✓
	International Migration		✓
Observations		438	438
Estimation Method		OLS	IV
F-test (First Stage, Δ Log Wage)		–	8.12
F-test (First Stage, Δ Log Rent)		–	5.56

Notes: The table reports estimates of equation (21). Column (1) presents OLS estimates, while column (2) reports IV estimates. All specifications include college fixed effects, city amenities, the local sum of exposure shares, and changes in international migration at the industry level weighted by local exposure shares (Borusyak, Hull and Jaravel 2024). Heteroskedasticity-robust standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table D4: Utility cost of moving

Year	Education	100km	500km	1,000km	1,500km	2,000km
1980	College	5.740	1.252	0.352	0.207	0.097
1990	College	5.931	1.218	0.337	0.202	0.110
2000	College	6.108	1.249	0.379	0.093	0.059
2011	College	6.754	1.357	0.367	0.068	0.066
2019	College	6.731	1.342	0.362	0.081	0.002
1980	Non-college	7.133	1.182	0.418	-0.261	0.403
1990	Non-college	7.007	1.272	0.491	-0.347	0.515
2000	Non-college	7.116	1.258	0.461	-0.236	0.359
2011	Non-college	7.358	1.543	0.51	-0.125	0.481
2019	Non-college	7.250	1.562	0.569	-0.212	0.413

Notes: The table shows parameter estimates of the moving cost function specified in Equation (16). Each parameter represents the utility cost increment for moves above the threshold of m kilometers.

Table D5: Utility cost of switching industries

Year	Education	$\delta^e_{0.05,t}$	$\delta^e_{0.3,t}$	$\delta^e_{0.8,t}$	$\delta^e_{1.5,t}$	$\delta^e_{2,t}$	$\delta^e_{4,t}$
1980	College	6.599	0.276	0.13	-0.001	0.13	0.251
1990	College	6.072	0.39	0.15	0.148	-0.002	0.593
2000	College	5.847	0.519	0.055	0.18	0.105	0.28
2011	College	5.845	0.479	0.042	0.245	0.04	0.414
2019	College	5.395	0.471	0.027	0.402	0.051	0.48
1980	Non-college	6.973	0.198	0.003	0.157	-0.132	0.579
1990	Non-college	6.266	0.211	0.113	0.062	0.162	0.537
2000	Non-college	6.187	-0.039	0.236	0.13	0.164	0.679
2011	Non-college	6.175	-0.038	0.21	0.139	0.202	0.458
2019	Non-college	5.691	0.043	0.188	0.249	0.216	0.437

Notes: The table shows parameter estimates of the switching cost function specified in equation (19). Each parameter represents the utility cost increment for task distances above the specified thresholds.

Table D6: Parameter estimates

	Observations	Mean	SD	Min	Max
Labor Supply					
Unobserved amenities Non-college ξ^n 1980	15,122	28.622	1.807	13.282	37.495
Unobserved amenities College ξ^c 1980	15,122	139.235	2.598	126.592	151.090
Unobserved amenities Non-college ξ^n 2019	25,032	29.851	2.385	8.916	39.626
Unobserved amenities College ξ^c 2019	25,032	220.499	3.073	200.216	235.327
Labor Demand					
TFP parameters A_{jkt} 1980	15,122	38638.589	12301.891	11936.631	156,724.786
TFP parameters A_{jkt} 2019	25,032	117338.214	46266.094	27630.137	902,489.988
Agglomeration constant a_{jkt} 1980	15,122	10.203	0.213	9.610	10.660
Agglomeration constant a_{jkt} 2019	25,032	11.273	0.217	10.693	11.743
Factor Non-college θ^n 1980	15,122	0.579	0.148	0.049	0.950
Factor College θ^c 1980	15,122	0.579	0.148	0.049	0.950
Factor Non-college θ^n 2019	25,032	0.507	0.167	0.022	0.979
Factor College θ^c 2019	25,032	0.507	0.167	0.022	0.979
Housing Supply					
κ_{jt} 1980	15,122	63.249	134.974	0.000	1,257.369
κ_{jt} 2019	25,032	189.560	403.763	0.000	4,026.005