Dynamic Migration:
From Local Effects to Aggregate Implications *

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Abstract

What are the local and aggregate dynamic effects of regional migration flows? To study this question, I use a panel SVAR structure and a shift-share instrument to analyze the short-, medium-, and long-term effects of a 1% increase in migration to US commuting zones. I construct the instrument using lagged birth rates from the areas that sent migrants each year. The estimates show that these inflows have positive and persistent effects on wages and productivity, though the magnitude of these responses depends on both time and population density. This suggests that the positive and negative spillovers of population size appear at different points following the shock, depending on factors such as housing supply and mobility costs. To explore the potential aggregate repercussions of these local factors, I construct a dynamic spatial economic model that accounts for regional migration frictions and productivity externalities. I then estimate the model parameters using the structural impulse responses from the panel SVAR and consider a two counterfactual scenarios: a removal and a reallocation workers across space. The results indicate misallocation and drops in labor supply can have important and persistent dynamic effects that vary over time.

Keywords: Scale Effects, Labor Mobility, Economic Growth

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1 Introduction

What are the aggregate dynamic effects of local migration flows? This paper answers this question by connecting the dynamic effects of local population inflows, to the macroeconomic implications of spatial labor sorting. On the one hand, spatial models with agglomeration economies predict that economic activity will concentrate in certain regions, drawing in workers seeking higher wages and amenities. In these frameworks, regional productivity tends to increase with larger populations. On the other, congestion forces can make highly populated areas less attractive due to higher land prices and lower-quality amenities, among other factors. Past studies provided empirical evidence of these effects. However, most of the literature so far focused on larger markets and specific time intervals, without necessarily connecting them to the aggregate economy.

As a first step towards filling this gap, in this study I analyze the reaction of local economic conditions in US commuting zones (CZ) to a 1% increase in migration inflows over multiple years. Understanding the response of variables such as real wages and housing prices measures over time is important for several reasons. First, a dynamic model enables us to account for factors that take longer to adjust, such as the number of establishments in an area or the skills workers acquire. Second, by analyzing the shape of the impulse response functions (IRFs), we can infer when agglomeration externalities overcome negative spillovers as well as the moment when the latter start to reduce productivity and wages. Finally, from a structural perspective, some mechanisms affect the immediate effect whereas others may only play a role in longer term responses, such as the creation of new firms and establishments. Therefore, the estimates from several periods can help identify the prevalence of each of these separately.

Indeed I find that output, wages, and employment all increase initially and peak 4 years after the initial migration shock. However, this cumulative effect then decreases slightly and stabilizes, with each outcome remaining at a higher permanent level. This is also the case for housing prices, which rise to 1.1% after 4 years, but then decrease to a level that is 0.9% higher than before the shock. The only variable that experiences a drop is the number of establishments per worker, which remains 0.15% lower after 8 years. A lower productivity response in the long term, relative to the medium term, suggests congestion externalities surpass agglomeration economies after 4 years, whereas the opposite is the case in the short- and medium-term. This is even more apparent when we look at the effect on net inflows, which are higher upon impact and then decrease as negative population spillovers deter new migrants from moving into a CZ.

To obtain these causal effects, I estimate a panel SVAR-IV model with shift-share instruments based on lagged birth rates. The vector autoregression structure allows me to capture the intertemporal relation between population inflows and all other variables of interest. Consequently, I not only account for the impact the former has on the latter but also for the influence favorable economic conditions might have on migration rates. After estimating the reduced-form panel VAR, I follow the methodology described in Stock and Watson (2018) and identify the impact of structural market size shocks using an external instrumental variable. Specifically, for each CZ I predict changes in population inflows using the lagged birth rates (by 25 years) of counties sending residents to that particular labor market, similar to Karahan, Pugsley and Şahin (2019).

Following the strategy used in the immigration literature, such as in Altonji and Card (1991) and Card (2001), the weights correspond to the lagged share of migrants coming from that area. However, in contrast to most studies in this field, I use migration patterns in the previous year and not a pre-period. Although these shares are potentially endogenous, I follow Borusyak, Hull and Jaravel (2022) and estimate the shift-share IV at the shock level, which in this case is at the level of the county sending migrants. Therefore I can rely on the exogeneity of past birth rates and construct a stronger instrument with inflow shares that better predict current migration changes. Furthermore, this shock-level approach allows me to compute the appropriate standard errors for inference thereby avoiding the drawbacks discussed in Adao, Kolesár and Morales (2019), which apply to conventional shift-share methods.

I also provide further evidence to better understand the mechanisms driving the baseline results. First, I split the CZs in my sample according to population per square mile and re-estimate the SVAR for each group. The new IRFs show that, although the magnitude of the estimate increases with CZ density, its variance does so as well, which suggests the net effect from the agglomeration and congestion externalities becomes more ambiguous. Furthermore, since the instrument is positively correlated with income per capita among migrants, a simple composition effect could be behind the rise in wages. Nevertheless, when I look at the response of wages within narrowly defined sectors with homogeneous low-skill requirements, I find that all of them experience a sustained increase.

Given these results, how does aggregate productivity react to worker mobility across space? Inherently, this question connects treatments at the local level to aggregate outcomes and answering it requires a theoretical framework. I therefore develop a dynamic spatial economic model in which forward looking workers choose where to live each period, subject to mobility costs on the intensive and extensive margin. In addition to these frictions, the model includes static agglomeration externalities à la Romer (1990) as well as local dynamic spillovers similar to the ones in Peters (2022), where fixed costs of production decrease with past population. Furthermore, a housing sector with fixed land and endogenously congested amenities make locations less attractive as population increases. The interaction of all these elements allows for a lasting effect of market size on economic outcomes through long-run elasticities, which can be different from the ones in the short-run as shown in the SVAR-IV estimates.

To discipline the main parameters of the model I use impulse response matching. In particular, I simulate the transition path of the economy implied by the empirical birth rates in the shift-share instrument. I then replicate the estimation described above using the simulated data to obtain model generated IRFs. The parameter estimates I obtain are the ones that minimize the distance between these simulated moments and the empirical version I estimated previously. This guarantees the model generates the correct causal effect of migration inflows on variables such as housing prices and output per worker. Other parameters are estimated using calibration by targeting cross-sectional evidence with moments generated in the initial steady-state.

I then use the calibrated model to answer the initial question and determine the importance of the spatial allocation of labor for aggregate dynamics. To accomplish this, I set up two policy counterfactuals: a labor "reduction" as well as a "reallocation" shock. Using the empirical geographical distribution of undocumented migrants in the US, the first exercise removes workers from the economy similar to what a deportation policy would result in. The second, on the other hand, redistributes them uniformly to other regions. By comparing both policies, I can distinguish the effects of misallocation from those coming due to a lower overall labor force. Indeed the first type of shock leads to a lower output per capita in the long run, with a steady decline following the removal. Although the "reallocation" shock does not have this long run level effect, it takes a long time to recover (even longer than population) since the mass of firms is a slow-moving variable.

Related literature This paper follows previous research on market size, labor mobility, and economic growth. From a theoretical perspective, Duranton and Puga (2004) summarize the main mechanisms driving agglomeration economies. The first of these is *sharing*: producers in larger cities can divide the fixed cost of indivisible inputs as well as the gains of specialization. Another channel is *matching*, as a larger labor force increases both the quantity and quality of firm-worker matches, especially in the presence of mismatching costs due to skill heterogeneity. Finally *learning* from a larger and more diverse market raises productivity through knowledge creation, diffusion, and accumulation (Lucas, 1988; Moretti, 2004; Crews, 2023). The relevance of each mechanism, and ultimately the effect of immigration, depends on the time frame. For example, a fixed capital stock in the short run causes wages to drop in the immediate years following worker inflows (Borjas, 2013). By estimating a dynamic model over several years, the following analysis determines how the relative importance of each mechanism evolves.

Numerous empirical studies estimate the response to labor inflows and obtain ambiguous results. Using previous immigration shares as an instrument, some papers find a negative effect on native employment and wages (Altonji and Card, 1991; Card, 2001). Similarly, the wage elasticities estimated by Borjas (2003) imply immigration to the US in the 1980s and 1990s reduced wages by 3.2%. Nevertheless, as the survey by Edo (2019) points out, the estimated impact on wages, employment, and other outcomes depends on the methodology, period, and country under study. Some papers have found evidence of agglomeration economies with positive spillovers on manufacturing productivity (Greenstone, Hornbeck and Moretti, 2010; Kline and Moretti, 2014) as well as employment opportunities (Moretti, 2010). Most of these studies estimate a single elasticity for multiple periods and adopt reduced-form strategies that do not account for the intertemporal correlation between migration and other economic measures.

To incorporate these interactions, this paper models local population inflows and outflows, along with other outcome variables, using a panel VAR structure. Barcellos (2010) adopted this approach in her analysis of migration between US states whereas Boubtane, Coulibaly and Rault (2013) did so for 22 OECD countries. To identify the dynamic response to population inflow shocks, these studies rely on ordering assumptions and Cholesky decompositions of the variance-covariance matrix. I avoid making such assumptions by estimating the coefficients of interest using an IV strategy as described by Stock and Watson (2018) and applied in the fiscal multipliers (Mertens and Ravn, 2013) as well as the monetary policy literature (Gertler and Karadi, 2015).

The use of exogenous variation resembles the analysis of previous authors leveraging historical episodes to estimate the effect of population movements. Notable examples include Peters (2022) and Burchardi and Hassan (2013), both of whom examine the impact of post-WWII German migrants who resettled in West Germany. However, their estimation relies on a single event, whereas the SVAR-IV exploits changes across time. To accomplish this, I use a shift-share instrument (estimated at the shock level as stated in Borusyak, Hull and Jaravel (2022)) based on migration shares and lagged birthrates. This follows a similar identification strategy as the one proposed by previous work that estimates the effect of increasing labor supply (Shimer, 2001; Karahan, Pugsley and Şahin, 2019).

The methodology in this paper identifies exogenous shocks that influence local in-migration flows to estimate the latter's effect on economic conditions. In this sense, it closely resembles the Local Projection IV (LP-IV) used in Howard (2020), which uses a dynamic model along with an Altonji and Card (1991)-style instrument to determine the effect of migration on unemployment. The paper finds that unemployment falls whereas the employment-to-population ratio rises. However, it differs from the analysis I carry out in several ways. First, its econometric approach does not account for the interaction between migration, unemployment, and other relevant variables such as wages, output, and establishments, which is an element the VAR structure allows me to consider. Furthermore, it only estimates the effect on labor market outcomes, whereas this paper determines the response on a set of comprehensive economic measures. Finally, I estimate the impact on CZs which cover a broader geographical sample than MSAs, which are only representative of urban economies.

This paper also follows previous work on the implications of local dynamics for aggregate outcomes. Davis, Fisher and Whited (2014) study the contribution of agglomeration in cities to aggregate productivity growth through the lens of a structurally estimated spatial model. In their framework, local output per worker depends positively on output density. Crews (2023) further endogenizes these externalities in a heterogeneous agents model: as the aggregate stock of skill in a city increases, the rate of individual human capital accumulation rises as well[1]. On the other hand, Peters (2022) proposes a different mechanism by relating current fixed costs of entry to past market size, creating dynamic spillovers. He embeds this in a model with variety gains, as in Romer (1990), and uses it to examine the scale effects on productivity in the context of postwar Germany.

The rest of the paper is structured as follows. The next section explains the SVAR-IV methodology, as well as the shock-level shift-share instrument I use to estimate the effects of migration. Then, in Section 3, I analyze the structural impulse responses to a 1% increase in inflows and discuss further supporting evidence. Section 4 develops the formal framework relating the local evidence to aggregate outcomes, whereas Section 5 implements the structural estimation of the model parameters. Finally Section 6 implements the policy counterfactuals and Section 7 concludes.

2 Econometric Model

2.1 Panel SVAR-IV Model

The first part of this paper seeks to determine the dynamic effect of population inflows on local economies. Specifically, for any CZ i and year t, I determine the impact total in-migration from within the US m_{it} has on the population flow dynamics in the years following the initial shock. In other words, I estimate the effect on future in- and out-migration rates, m_{it} and o_{it} respectively, since the arrival of new residents could drive native workers to leave as well as more immigrants to relocate in the future. This could be due, in part, to changes in employment opportunities. Consequently, I also study the effect on the employment-to-population ratio l_{it} to establish if new workers compete for the same jobs as previous employees or if their arrival leads to additional opportunities.

Another relevant labor market outcome is the average wage within a CZ w_{it}, as an in-migration shock can increase labor supply and could therefore lower salaries. On the contrary, the presence of agglomeration economies can make labor productivity increase with larger market size. These two opposing effects can lead to different net impacts across different timelines. In addition to wages, I also estimate the effect on output per worker y_{it}, another measure of aggregate productivity, as well as on the number of establishments

[1] Previous papers in the growth literature suggested this mechanism (Uzawa, 1965; Lucas, 1988), albeit at an aggregate level in a representative agent economy.

per worker k_{it}. Through the lens of an expanding variety model, a larger workforce leads to higher entry, which in turn increases productivity. Thus, accounting for establishments will allow me to test the predictions of such frameworks.

Finally, I determine the response of housing prices hp_{it}, a major component of households' local expenditures. As the population of an area increases, these values should increase in the short run, when the good is in fixed supply. This would in turn act as a congestion force, counteracting the agglomeration externalities and therefore leading to different effects across timelines. Moreover, recent trends in real estate prices, especially in markets experiencing a high inflow of migrants, have prompted a policy discussion aimed at increasing the housing supply. Consequently, to study these counterfactual policies we first need to estimate the effect of population increases on real estate values.

To estimate these effects, the first step is to model these variables using a panel SVAR structure, similar to the one in Boubtane, Coulibaly and Rault (2013), which accounts for the reciprocal relation between population flows and economic performance in a given geographical area. In this sense, define a vector of stationary observables $\boldsymbol{Y}_{it}$[2] and assume it follows a linear process:

$$\boldsymbol{A} \cdot \boldsymbol{Y}_{it} = \sum_{l=1}^{p} \boldsymbol{\alpha}_l \cdot \boldsymbol{Y}_{it-l} + \boldsymbol{\varepsilon}_{it} \tag{1}$$

where $\boldsymbol{A}$ is a non-singular matrix. Furthermore, $\boldsymbol{\varepsilon}_{it}$ is a vector of structural innovations uncorrelated across localities and time, with $E[\boldsymbol{\varepsilon}_{it}] = 0$ and $E[\boldsymbol{\varepsilon}_{it}\boldsymbol{\varepsilon}'_{it}] = I$. The reduced form of the model above is given by:

$$\boldsymbol{Y}_{it} = \sum_{l=1}^{p} \boldsymbol{\delta}_l \cdot \boldsymbol{Y}_{it-l} + \boldsymbol{B}\boldsymbol{\varepsilon}_{it} \tag{2}$$

where $\boldsymbol{B} = \boldsymbol{A}^{-1}$ and $\boldsymbol{\delta}_1 = \boldsymbol{A}^{-1}\boldsymbol{\alpha}_1$.

Define $\boldsymbol{u}_{it} = \boldsymbol{B}\boldsymbol{\varepsilon}_{it}$ as the reduced-form residuals. After estimating equation (2) we need to identify $\boldsymbol{B}$ to construct impulse responses to structural migration shocks ε^m_{it}. Typically, when making timing assumptions, we would rely on the Cholesky decomposition of Σ, the covariance matrix of $\boldsymbol{e}_{it}$, to achieve this. This is the approach Boubtane, Coulibaly and Rault (2013) adopt in their analysis of OECD immigration. However, since I am only interested in the response to immigration shocks, and given the ordering of variables in $\boldsymbol{Y}_{it}$, I only need to identify the first column $\boldsymbol{b}^m$. By instead using instrumental variables as detailed in Stock and Watson (2018), I avoid imposing any timing or sign restrictions.

To see this, rewrite the reduced-form residuals of the j^{th} VAR equation as a function of the structural migration ε^m_{it} and non-migration $\boldsymbol{\varepsilon}^{-m}_{it}$ shocks:

$$u^j_{it} = b^m_j \cdot \varepsilon^m_{it} + \boldsymbol{b}'_{j,2:5} \cdot \boldsymbol{\varepsilon}^{-m}_{it} \tag{3}$$

[2] This includes all the variables discussed above so that $\boldsymbol{Y}_{it} = [\Delta m_{it}, \Delta o_{it}, \Delta y_{it}, \Delta w_{it}, \Delta l_{it}, \Delta k_{it}, \Delta hp_{it}]'$.

where b_j^m corresponds to the first coefficient in the j^{th} row of matrix $\boldsymbol{B}$. If we use a unit-effect normalization, so that $b_m^m = 1$, we can substitute ε_{it}^m with the residuals from the migration equation and obtain:

$$u_{it}^j = b_j^m \cdot u_{it}^m + e_{it}^j \tag{4}$$

where e_{it}^j is a linear combination of the non-migration structural shocks $\boldsymbol{\varepsilon}_{it}^{-m}$.

As Stock and Watson (2018) note, although the residuals u_{it}^j are unobserved, to estimate b_j^m we can use each equation in the reduced-form VAR in (2) to rewrite equation (4) as[3]:

$$Y_{it}^j = b_j^m \cdot m_{it} + \sum_{l=1}^{p} \boldsymbol{\Gamma}_l^j \cdot \boldsymbol{Y}_{it-l} + e_{it}^j \tag{5}$$

where Y_{it}^j is the j^{th} entry in $\boldsymbol{Y}_{it}$. Since in-migration rates m_{it} are correlated with non-migration shocks we have $E[m_{it}^m e_{it}^j] \neq 0$. Consequently, estimating the coefficients of interest requires a vector of instruments $\boldsymbol{z}_{it}$ that satisfies the relevance and exclusion conditions, $E[\varepsilon_{it}^m \boldsymbol{z}_{it}] \neq 0$ & $E[\varepsilon_{it}^{-m} \boldsymbol{z}_{it}] = 0$ respectively. With these instruments, I can estimate equation (5) using two-stage least squares, recover column $\boldsymbol{b}^m$ and finally compute the dynamic response of all the local economic variables in $\boldsymbol{Y}_{it}$ to a structural population inflow shock ε_{it}^m.

2.2 Shift-Share Instruments

To identify the effect of structural market size shocks using the methodology above, I construct a set of Altonji and Card (1991)-style instruments z_{it}^g, based on migration shares s_{int} and demographic shocks g_{nt}:

$$z_{it}^g = \sum_n s_{int} \cdot g_{nt} \tag{6}$$

where n is the county from which migrants originate. To see how this instrument captures variation in market size, note that we can decompose population growth $\Delta \ln N_{it}$ as:

$$\Delta \ln N_{it} \approx \frac{\Delta N_{it-1}}{N_{it-1}} + \frac{\Delta b_{it}^{net}}{N_{it-1}} + \underbrace{\sum_n \left(\frac{\tilde{m}_{int-1}}{N_{it-1}} \cdot \frac{\Delta \tilde{m}_{int}}{\tilde{m}_{int-1}} \right)}_{\text{In-migration rate } \Delta m_{it}} - \frac{\Delta \tilde{o}_{it}}{N_{it-1}} \tag{7}$$

where b_{it}^{net} is births net of deaths, $\tilde{m}_{int}$ is the total flow of migrants coming from n to i and $\tilde{o}_{it}$ is the total outflow of individuals from i.

We can see that the third term in equation (7) is the in-migration rate, which is decomposed into inflow shares and growth rates. I use the former to construct the instrument so

[3] From (2) we know $u_{it}^j = Y_{it}^j - \sum_{l=1}^{p} \boldsymbol{\delta}_l^j \cdot \boldsymbol{Y}_{it-l} - \nu_i^j - \nu_t^j$. Use this in (4) and define $\boldsymbol{\Gamma}_l^j = \boldsymbol{\delta}_l^j - b_j^m \boldsymbol{\delta}_l^m$ to obtain (5).

that $s_{int} = \tilde{m}_{int-1}/N_{it-1}$. This is the "pull" factor of migration: since individuals tend to move to places that previously received migrants coming from the same area, the share s_{int} "pulls" households from n to i. On the other hand, the "push" factor will be the demographic shocks that produce an outflow from n and proxy for the growth rates within the sum in equation (7). To this end, and following a similar strategy to Karahan, Pugsley and Şahin (2019) and Shimer (2001), I set g_{nt} equal to the 25-year lags of birth rates in county n.

Note that, unlike previous migration studies that use this type of instrument, the shares are lagged by one year instead of multiple periods. Although this produces a stronger instrument it also introduces endogeneity since the predictable element of current productivity could influence past migration shares. Nevertheless, I follow Borusyak, Hull and Jaravel (2022) and estimate the IV regression at the *shock-level*, which in this case is at the county of origin level. Thus for each dependent variable Y^j_{it} in the VAR, instead of estimating equation (5), I use the following specification:

$$\bar{Y}^{j\perp}_{nt} = b^m_j \cdot \bar{m}^{\perp}_{nt} + \bar{e}^{j\perp}_{nt} \tag{8}$$

where, for every variable x, we have $x^{\perp}$ is the residual from a regression of x_{it} on the original controls, including the lagged values of Y^j_{it}, and $\bar{x}^{\perp}_{nt} = \sum_i \frac{s_{int}}{s_{nt}} x^{\perp}_{it}$.

In addition to recovering the same coefficient of interest b^j_m, this specification has other benefits. On the one hand, it recovers the appropriate standard errors and therefore avoids the issues with classic shift-share designs shown in Adao, Kolesár and Morales (2019), such as the potential correlation between residuals and instruments across observations. Furthermore, this method relies on the exogeneity of the shock g_{nt} and not that of s_{int}, which is why I can use migration shares from the previous period to strengthen the instrument.

To satisfy this exclusion restriction, birth rates 25 years ago in counties sending migrants need to be exogenous to unobservable variables affecting the current dependent variables in destinations. Specifically, following Borusyak, Hull and Jaravel (2022), $\bar{e}^j_{nt}$ is the average unobserved shock to variable j (for example wages) across CZs that are mostly receiving migrants from n. Lagged birth rates need to be uncorrelated with these unobservable shocks. This would be violated if, for example, individuals making fertility decisions could predict economic conditions 25 years in the future in the counties receiving the most migrants after that time interval. Aggregate shocks, such as booms and recessions, as well as permanent productivity differences, are controlled for by time fixed effects and using differenced variables respectively.

2.3 Data

The IRS provides annual Statistics of Income (SOI), which include county-to-county population flows from 1990 to 2018. Specifically, for any origin i and destination j in year t, we observe the number of individual income tax returns that changed addresses from i in $t-1$ to j in t. This dataset also includes the number of exemptions as well as the total adjusted gross income associated with those returns. Following IRS guidance, the first variable proxies for the number of households that move from one county to another whereas the second represents the number of individuals that do so. Consequently, I define the migration rate into county i as:

$$m_{it} = \frac{\text{Total Exemption Inflow from USA Counties}_{i,t}}{\text{Population}_{i,t-1}}$$

where I obtain population from the BEA. I also define the outflow rate o_{it} in a similar manner.

The BEA also provides GDP, wages, and employment at the county level, which are some of the variables in $\boldsymbol{Y}_{it}$[4]. This data is available from 2001 to 2019. Furthermore, I obtain the number of establishments for each county from the Business Dynamics Statistics (BDS) produced by the Census Bureau. To aggregate all these measures at the CZ level, I use the USDA ERS definitions from 2000, which map each county to one of 709 CZs. As described in Autor and Dorn (2013), these geographic areas group counties with strong commuting ties, and therefore constitute a better unit of analysis for studying the local effects of migration. Furthermore, unlike metropolitan areas that only cover certain locations, CZs encompass the entire continental US. Finally, to find housing price growth Δhp_{it}, I use the FHFA house price index, which is available at the county level. Therefore, I use the same delineation of CZs to compute an average housing index growth rate, weighted by the population of each county within a commuting zone. Table 1 shows the descriptive statistics for these variables.

To construct the instrument I need birth rates at the county level. I obtain this from the CDC's National Vital Statistics microdata, which provides details on each birth during the calendar year[5]. Once I build the instrument I observe how it correlates with migrant income. The left panel of Figure 1 shows how the instrument is positively correlated with the absolute income per capita among households arriving to CZs. In other words, this suggest the "push" and "pull" factors are associated with high income migration. However, when we control for the average wage at the destination this relationship becomes flatter,

[4]GDP figures correspond to CAGDP2 whereas the remaining BEA variables come from the Economic Profile for counties (CAINC30)

[5]This data is publicly available for all counties until 1988. From 1989 onwards, I only have the number of births for counties with a population over 100,000 (which corresponds to 500 counties). Consequently, I impute the missing births using the average share (out of all state births) for each county for previous years.

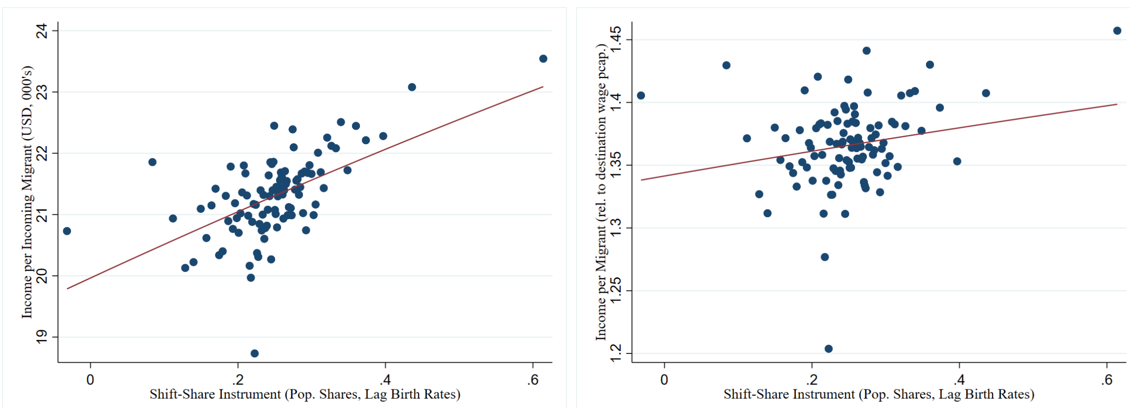
Table 1 Descriptive Statistics

Commuting Zones	Mean	St. Dev.	10%	50%	90%
Inflow Rate (%)	1.61	1.25	0.60	1.37	2.77
Outflow Rate (%)	1.63	1.39	0.75	1.48	2.56
Net Immigration Rate (%)	-0.02	1.27	-0.49	-0.07	0.48
Employment-to-population	0.42	0.07	0.33	0.42	0.52
GDP per worker (000's)	98.85	36.02	75.44	91.68	124.06
Average Wage (000's)	37.55	6.89	30.70	36.15	45.85

Note: Sample consists of 660 commuting zones within the continental US (excluding Alaska) and years 2002-2018.

as evidenced by the right panel of the same figure.

Figure 1. Migrant Income & Shift-share Instrument



(A) Migrant income (absolute) & instrument

(B) Migrant income (relative) & instrument

Note: Each figure is a binned scatter plot with 100 bins. Controls for year and commuting zone fixed effects.

3 Empirical Results

The first subsection estimates the SVAR-IV model described above on the entire sample. The result is a set of structural impulse responses that show the evolution of local economies after a 1% increase in the migration rate. The remaining parts of this section delve deeper into these effects by studying the heterogeneity across different types of commuting zones as well as the impact on wages in several service industries.

3.1 Baseline SVAR-IV

The shift-share structure of the instrument allows any type of shock at the origin county level g_{nt} that is exogenous with current economic conditions. Consequently, I compare lagged birth rates with other demographic "push" factors in Table 2. The first is the total outflow from county n: note from equation (7), this effectively replaces the specific migration flow from n to i with the total number of people leaving n. This explains why this county-level shock produces a stronger instrument than the other two, with an F-statistic of 81.96[6] when combined with the migration-to-population shares found in equation (7). Nevertheless, this variable is the least likely to be uncorrelated with current unobservable economic shocks affecting destinations.

Table 2 Shock-level IV First Stage

	Δm_{it} (1)	Δm_{it} (2)	Δm_{it} (3)	Δm_{it} (4)	Δm_{it} (5)	Δm_{it} (6)
z_{it}^{outflow}	74.90***	190.21***				
	(8.27)	(39.97)				
$z_{it}^{\text{pop. growth}}$			269.63***	12484.44*		
			(67.39)	(4974.16)		
$z_{it}^{\text{birth rate (25y ago)}}$					0.31*	26.12***
					(0.12)	(6.58)
# of destination-years	8,232	8,232	8,232	8,232	8,232	8,232
# of origin-years	11,241	11,241	11,357	11,357	11,357	11,357
F-stat	81.960	22.642	16.006	6.299	6.193	15.759
Shares relative to total migration	✓		✓		✓	
Shares relative to total population		✓		✓		✓

Note: Robust standard errors clustered at the originating county level in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; All regressions control for the lagged values of the variables in $\boldsymbol{Y}_{it}$ and contain time fixed effects. Year range is 2002-2018. For each shock (total outflow, population growth and lagged birth rate), this table reports two sets of first stage results as a robustness check. The first uses an instrument based on the share of migration from n to i relative to total migration $\tilde{m}_{int-1}/m_{it-1}$. The second is the migration-to-population share $\tilde{m}_{int-1}/N_{it-1}$.

Another county level "push" variable we can use is the total population growth rate in origin n. As column (4) in Table 2 shows, the resulting instrument is highly correlated with in-migration growth, with the highest coefficient among all three shocks. The increasing population in origin counties produces a higher outflow that gets allocated according to the migration shares. Nevertheless, its F-statistic of approximately 6.3 makes this a weak instrument. Furthermore, although total population growth is more likely to satisfy the exclusion restriction than total outflow, it can still suffer from endogeneity as it is not a lagged variable.

Finally, Table 2 also reports the first stage for the instrument that uses lagged birth rates, which is the one I use to compute the baseline IRFs later in this paper. As column (6) shows, as z_{it}^{birth} increases so does the growth rate of migration inflows. Furthermore, this coefficient is statistically significant and possesses an F-statistic of 15.76. These results,

[6] All the first stage results, including the F-statistic come from the *shock-level* regression developed by Borusyak, Hull and Jaravel (2022).

along with the arguments provided in the previous section, make this third instrument the preferred variable for estimating the response to a structural migration shock.

TABLE 3 SHOCK-LEVEL SSIV

	Δo_{it}		Δy_{it}		Δw_{it}		Δl_{it}		Δk_{it}		Δhp_{it}	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δm_{it}	0.516***	0.123	0.001	0.141*	0.005***	0.091**	0.005***	0.125***	-0.002	-0.117**	0.004**	0.535***
	(0.038)	(0.174)	(0.003)	(0.064)	(0.001)	(0.029)	(0.001)	(0.036)	(0.001)	(0.036)	(0.001)	(0.144)
# of destination-years	10,258	8,232	10,258	8,232	10,258	8,232	10,258	8,232	10,258	8,232	10,258	8,232
# of origin-years		11,357		11,357		11,357		11,357		11,357		11,357

Note: Robust standard errors clustered at the originating county level in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; All regressions control for the lagged values of the variables in $\boldsymbol{Y}_{it}$ and contain time fixed effects. Year range is 2002-2018.

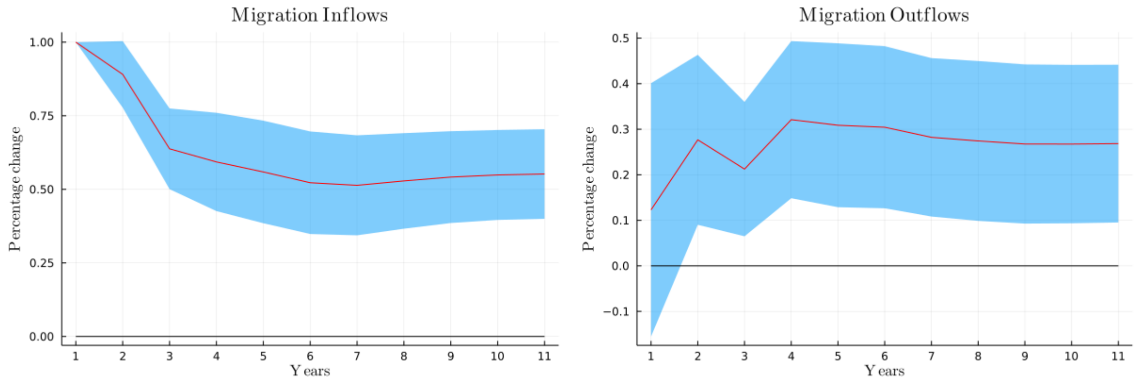
Indeed, Table 3 shows the results from the two-stage least squares estimation using the birth rate instruments. Recall these estimates correspond to the first column of matrix $\boldsymbol{B}$ in equation (2). As such, they identify the initial response of each variable to a migration inflow shock $\boldsymbol{\varepsilon}_{it}^{m}$. In this sense, we can see that outflows initially rise after an increase in inflows. However, when comparing them with the OLS estimates, we can see the true effect is lower and statistically not significant. The upward bias could be due to unaccounted shocks (in the OLS case) that are positively correlated with both inflows and outflows, such as shifts in the local production process that benefit workers from other counties who replace established residents.

On the other hand, the contemporaneous response of output and wages is statistically significant and higher when using the instrument as seen in columns (4) and (6). While GDP per worker increases by 0.14%, average salaries do so by 0.09%, which suggests the 1% rise of in-migration mostly represents a demand shock that is passed through from the goods to the labor market. Additionally, the agglomeration externalities discussed in the introduction could be present upon impact. These mechanisms would also explain the rise in employment of 0.13% in column (8). Unobserved variables, such as changes in industrial composition that benefit native residents over incoming migrants while still increasing productivity, could be driving the downward bias in the OLS measures.

Finally, the number of establishments per worker drops by -0.12% while housing prices experience a rise of 0.54%, the highest increase of all 7 variables. Thus existing establishments absorb the arrival of new workers by creating new positions since the employment-to-population rises as we saw above. On the other hand, the direction and magnitude of the real estate response reveal a potential congestion effect that could counteract the demand shock driving wage and productivity growth in the medium to long run. To evaluate this, we now study the structural impulse responses.

After a 1% increase in the migration rate, the net inflow of commuting zones increases and remains high after several years. Figure 2 decomposes this effect into inflows and outflows following the initial shock. On the one hand, more people leave the area even after

Figure 2. Cumulative IRFs for migration flows



Note: The red line represents the cumulative impulse response. The blue shade indicates a 90% confidence level. Standard errors are generated by Monte-Carlo with 200 repetitions.

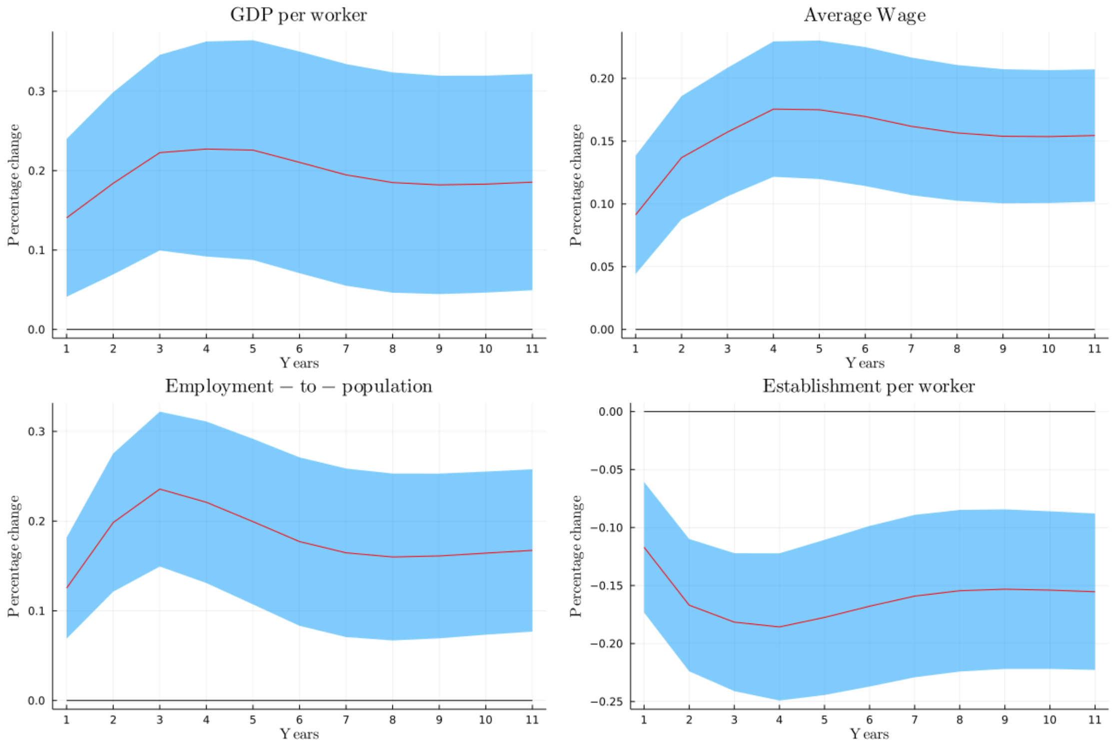
8 years. However, this is only 0.3% higher than it was before the first arrival. On the other hand, inflows permanently increase by 0.5%. Thus, although some workers decide to move from the CZ, maybe because the shock negatively impacts their salaries and employment prospects, enough individuals decide to move into the area to maintain a positive net inflow. It is important to note that the cumulative effect of in-migration is lower than the initial rise. As the population suddenly increases, this could hurt certain amenities (such as long-term residential costs as we will see later), which makes the destination less attractive to future migrants so that part of the initial shock fades out.

Since net inflows remain positive, the local market size continues to rise and therefore output and wages continue to increase as a response to surging demand. This occurs until they reach their peak between 3 and 4 years after the shock, as the top two panels of Figure 3 show. Notice all variables in the figure experience a medium run effect within the same time frame, as employment-to-population grows by 0.23% and the number of establishments per worker drops by 0.2%. During this time firms hire an increasing number of workers to meet demand, but this is also the period when longer-term agglomeration externalities, such as those described in Duranton and Puga (2004), can start affecting productivity.

Nevertheless, housing prices also grow in the medium term, exerting pressure on the budget constraint of residents. The cumulative impulse response in Figure 4 shows how these values are 1% higher once they reach their peak. This is a much larger effect than that of GDP per worker, which only grew by 0.2% in the same period. Consequently, newer migrants are discouraged from moving into the CZ and inflows fall as we saw before. The response of real estate values can also be a proxy for other unobservable negative externalities that also increase with population, such as traffic and pollution.

These are examples of the congestion forces that avoid a sustained rise in the in-migration rate. However, as time passes several factors can alleviate their negative effects. In the case of housing, growth in supply and new constructions can reduce the pressure

Figure 3. Cumulative IRFs for economic variables



Note: The red line represents the cumulative impulse response. The blue shade indicates a 90% confidence level. Standard errors are generated by Monte-Carlo with 200 repetitions.

on prices. This could be why we see a slight decline in Figure 4, after which values stabilize. Furthermore, since net inflows decreased from their initial level, at this point, the population is growing at a smaller rate as well as residential demand.

We can see the same pattern for the other variables in the VAR, with a long-run response that is smaller in magnitude than the one after 4 years. Output per worker, average wages, and the employment-to-population ratio all fall after their peak in Figure 3. Furthermore, the number of establishments rises slightly from its trough. The reason behind these responses is the same as the one we mentioned above: although the population is increasing, it is doing so at a lower rate. Presumably, this is the growth rate that balances agglomeration and congestion externalities. For example, if we consider wages, this is the market size growth rate at which the increase in demand and supply for labor offset one another.

3.2 Further Evidence

The previous results show the importance of studying the dynamic response of jointly distributed variables, as the short-, medium-, and long-run effects all differ. Now I explore whether these effects are heterogeneous across different types of CZs and industries, and if

FIGURE 4. CUMULATIVE IRFS FOR ECONOMIC VARIABLES

Note: The red line represents the cumulative impulse response. The blue shade indicates a 90% confidence level. Standard errors are generated by Monte-Carlo with 200 repetitions.

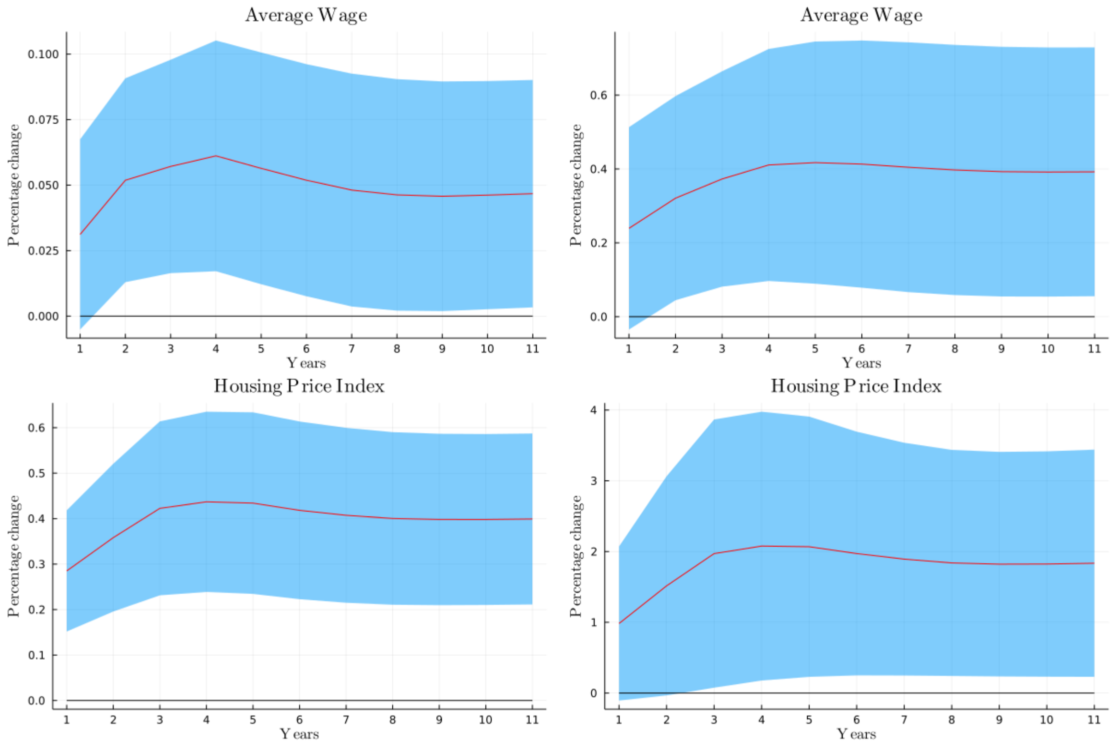
so what this reveals regarding the underlying mechanisms.

First, we can find the density of each CZ and determine whether the local effect changes depending on this factor. Specifically, I compute the average population for each zone throughout the years and classify each on whether they are in the bottom, medium or top third of the density distribution. I then re-estimate the SVAR-IV model specified above for each of these groups separately. The reason different densities could produce heterogeneous responses is the differential relevance of congestion and agglomeration forces. Workers in New York City interact with each other more frequently than those in Phoenix, where land is less densely populated, which facilitates the human capital externalities that Lucas (1988) described. Nevertheless, these areas also experience higher congestion, and therefore the net effect of migration shocks is ambiguous.

When we look at the plots by density in Figure 5 we can see the response in medium-density CZs is higher in magnitude than that in areas with a low population by square mile. The average wage, for example, reaches a peak that is 0.4% higher in the former whereas in the latter it only grows by 0.05%. This difference in magnitude suggests the agglomeration externalities that drive productivity increases are more prevalent in denser areas. One such mechanism is the acceleration of human capital accumulation in cities explored in Crews (2023). Another is misallocation: in sparse markets, it is less likely for workers with particular skills to supply their labor in the industry where they possess a comparative advantage. However, as the right plots in the figure show, the standard errors become wider with density. This could be due to congestion effects that mitigate the agglomeration externalities.

Recall from Figure 1 that migrant income is positively correlated with the instrument. Since the exogenous variation is coming from high-income migrants, the baseline results in

FIGURE 5. CIRFS FOR LOW AND MEDIUM DENSITY CZS



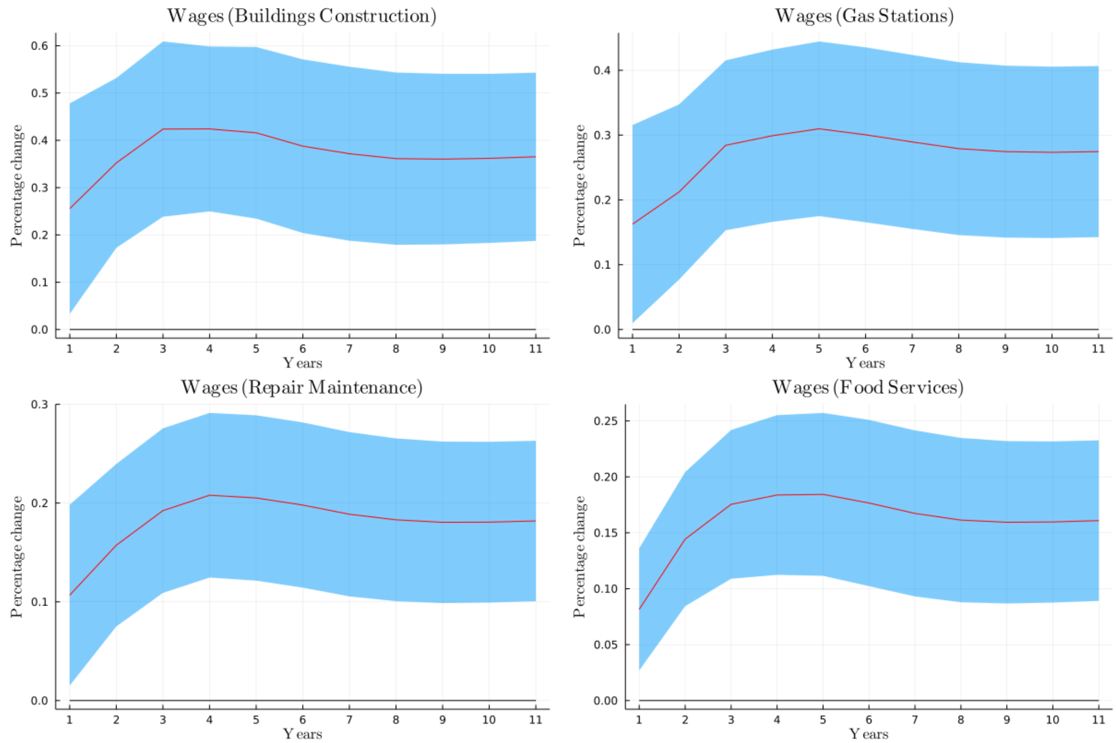
Note: The red line represents the cumulative impulse response. The blue shade indicates a 90% confidence level. Standard errors are generated by Monte-Carlo with 200 repetitions.

Figure 3, and especially the response of wages, could be due to a composition effect. To test this I estimate the path of wages after the shock within industries with homogeneous low-skill requirements. If we observe a change in these salaries, we can conclude the impact of in-migration is broad-based. To carry this out I select a set of 3-digit NAIC sectors and add each of their average wages to the VAR to re-estimate the model with 8 variables instead of 7[7]. I then plot the impulse response of each wage in Figure 6.

The results indeed suggest this is more than a composition effect. For reference, recall from the baseline responses that wages increased between 0.1% to 0.2%. As Figure 6 shows, this increase in salaries affects workers in a diverse set of industries. These include building construction and repair & maintenance services, where the impact is 0.4% and 0.2% at its peak respectively. Besides raising the average wage due to their higher income, incoming migrants increase the market size of CZs. This in turn produces a positive demand shock as well as triggering agglomeration externalities that affect services and non-tradable production. The following section explores these mechanisms quantitatively through the lens of a formal framework.

[7]Each of these industries will have a VAR model associated with it. The Quarterly Census of Employment and Wages (QCEW) provides average wages at the county-industry level. To aggregate them at the CZ level, I use the same delineation detailed in Section 2

Figure 6. CIRFs for wages across NAICs sectors



Note: The red line represents the cumulative impulse response. The blue shade indicates a 90% confidence level. Standard errors are generated by Monte-Carlo with 200 repetitions.

4 Theoretical Model

Increasing migration inflows by 1% produces a positive and sustained change in local economic outcomes such as wages, output and housing prices. However, the shape of the effect across time suggests the interaction between agglomeration and congestion externalities results in different effects at different intervals. To rationalize these results, this section develops a theoretical model that will later be disciplined with the structural impulse responses.

4.1 Environment

Households The economy consists of $g \in G$ regions in continuous time $t \in \mathbb{R}^+$ and a mass $N(t)$ of workers who discount the future at rate ρ and exit the labor force at regional rate δ. Furthermore, each period, workers enter the regional markets at an exogenous rate $b_g(t)$ are born. When they are born workers are endowed with a permanent productivity level $z \in \Omega_z$, which they draw from an initial distribution $z \sim F(z)$. They derive utility from consumption $C_g(t)$ and housing $H_g(t)$, as well as an amenity $D_g(t)$ so that:

$$U_g(C_g(t), H_g(t)) = D_g(t) \cdot C_g(t)^{\alpha} \cdot H_g(t)^{1-\alpha}$$

where $D_g(t) = D_g \cdot N_g(t)^{-\phi}$ and $\phi > 0$. Note that amenities are decreasing with local population. This is to account for congestion externalities other than housing such traffic or the public goods. The consumption good is a CES aggregate from differentiated regional varieties $C_g = (\sum_r c_{rg}^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}$. To buy variety r in g, households need to pay $p_{rg}(t)$, whereas $P^h_g(t)$ is the price for each unit of housing they consume.

Each period thereafter they receive a migration opportunity, whose arrival follows a Poisson process with rate λ[8]. This parameter captures the fixed costs associated with moving to new markets. This is one of the two mobility frictions the model includes. After receiving the migration opportunity, workers draw a preference shock for each location $\xi_g(t)$, which are distributed i.i.d. Frechet with shape parameter ν. The second friction is a flow-utility cost κ_{gd} that the household pays for moving from g to d, where $\kappa_{gd} < 1$ for $g \neq d$ and $\kappa_{gg} = 1$. Thus workers consider the value of living in each location, given these mobility costs and preference shocks that are both multiplicative and permanent as in Crews (2023).

The mobility decisions of workers, along with their entry and exit from the economy, will determine the spatial distribution of z at time t dennoted by $\psi_g(z,t)$. Thus the total labor available in region g will be given by

$$L_g(t) = N(t) \cdot \int_{z \in \Omega_z} z \cdot \psi_g(z,t) dz$$

since workers supply their efficiency units z inelastically in the region g they choose to live in, in exchange for the local wage $W_g(t)$. Additionally, the population of region g is determined by $N_g(t) = N(t) \cdot \int_{z \in \Omega_z} \psi_g(z,t)dz$.

Production Perfectly competitive local producers supply housing services $H_g(t)$ by combining land $T_g(t)$ and labor $L^h_g(t)$ as inputs using the following function:

$$H_g(t) = \Gamma_h T_g(t)^{\theta} (L^h_g(t))^{1-\theta}.$$

where $\Gamma_h = \theta^{-\theta}(1-\theta)^{-(1-\theta)}$. I assume land is a fixed factor owned by immobile landlords who collect rents $R_g(t)$.

Following Romer (1990), production of regional varieties is subject to variety gains. Each period, under perfect competition, a local firm sources $y_{gd}(j,t)$ at price $q_g(j,t)$ from firm j to produce y_{gd}, the amount of variety $g \in G$ it ships to destination d. These inputs are aggregated following:

$$y_{gd}(t) = \frac{1}{\tau_{gd}} \left(\int_0^{M_g(t)} y_{gd}(j,t)^{\frac{\varepsilon-1}{\varepsilon}} dj \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

[8] I assume that newborns do not receive this migration opportunity and are not subject to the exit probability.

where $M_g(t)$ is the mass of intermediate input producers in g at time t, and τ_{gd} represents the usual iceberg trade cost. Local intermediate producers on the other hand face monopolistic competition as well as labor requirements given by

$$l_g(j,t) = \frac{y_g(j,t)}{A_g} + F_g(t)$$

where A_g is the fixed productivity in region g and $F_g(t)$ is the fixed cost in terms of labor units that firms have to pay. Similar to the discrete time setting in Peters (2022), this related to the growth rate of the mass of firms as well as the *inter-temporal knowledge elasticity* η:

$$F_g(t) = \gamma_M(t) \cdot M_g(t)^{-\eta} \tag{9}$$

where $\gamma_M(t) = \dot{M}_g(t)/M_g(t)$.

4.2 Static Equilibrium

At any point in time t, the state variables for each geography $g \in G$ consist of the mass of producers $M_g(t)$ and the distribution of efficiency units $\psi_g(z,t)$. We can therefore define a static equilibrium as follows:

Definition 1. *For each $g \in G$, given $M_g(t)$ and $\psi_g(z,t)$, a **static equilibrium** in period $t \in \mathbb{R}_+$ is a set of prices and allocations for skill $\{W_g(t), L_g(t)\}$, consumption imported from all regions $\{c_{rg}(t), p_{rg}(t)\}_{r \in G}$, intermediate inputs $\{q_g(j,t), y_{gd}(j,t)\}_{j \in M_g(t), d \in G}$, housing $\{H_g(t), P_g^h(t)\}$ as well as land $\{T_g(t), R_g(t)\}$ such that given prices i) households and firms behave optimally, ii) allocations clear their respective markets.*

Given their place of residence, households decide how much to consume of each region's variety with a local price index given by $P_g(t) = (\sum_r p_{rg}(t)^{1-\sigma})^{1-\sigma}$. Worker z will spend a constant share of her income $v_g(z,t) = z \cdot W_g(t)$ on consumption goods and housing services. Since land is fixed the supply of housing services under perfect competition will be:

$$H_g(t) = \left(\frac{P_g^h(t)}{W_g(t)}\right)^{\frac{1-\theta}{\theta}} \cdot \frac{T_g}{\theta} \tag{10}$$

On the other hand, local producers decide how much of their output they allocate to each region (including their own) as well as the demand for local varieties, which will be

$$y_g(j,t) = \left(\frac{Q_g(t)}{q_g(j,t)}\right)^{\varepsilon} Y_g(t),$$

where $Y_g(t)$ is the total output of region g and $Q_g(t)$ is the price index these firms face. Intermediate producers take this demand and choose prices and labor so as to charge a markup over marginal cost $q_g(j,t) = \frac{\varepsilon}{\varepsilon-1} \cdot \frac{W_g(t)}{A_g}$, which implies $Q_g(t) = M_g(t)^{\frac{1}{1-\varepsilon}}(\frac{\varepsilon}{\varepsilon-1} \cdot \frac{W_g(t)}{A_g})$. Furthermore, free entry determines total labor demand for production in region g:

$$L_g^y(t) = \int_0^{M_g(t)} l_g(j,t)dj = M_g(t)F_g(t)\varepsilon \tag{11}$$

Market clearing for labor states demand from the goods and housing sector has to equal total supply $L_g(t)$. This, along with zero profits and housing market clearing, sets the total efficiency units in housing production as a constant share of regional labor: $L_g^h(t) = (1-\theta)(1-\alpha)L_g(t)$. Total income in region g is $W_g(t)L_g(t)$ and balanced trade implies:

$$W_g(t)L_g(t) = \sum_d \pi_{gd}(t)W_d(t)L_d(t) \tag{12}$$

where $\pi_{gd}(t)$ is the share of consumption expenditures in d spent in goods from g. This in turn is given by:

$$\pi_{gd}(t) = \frac{\Big(\tau_{gd} \cdot Q_g(t)\Big)^{1-\sigma}}{\sum_{i\in G}\Big(\tau_{id} \cdot Q_i(t)\Big)^{1-\sigma}} \tag{13}$$

Using equilibrium input prices I obtain the price index $P_g(t) = Q_g(t) \cdot \pi_{gg}(t)^{\frac{1}{\sigma-1}}$ as well as the price of housing units in region g given by:

$$P_g^h(t) = \left(\frac{(1-\alpha)\cdot L_g(t) \cdot \theta}{T_g}\right)^{\theta} \cdot W_g(t) \tag{14}$$

Combining them with the demand for consumption goods and housing, I derive the flow utility a worker with productivity level z receives when living in region g:

$$U_g(z,t) \quad = \quad \underbrace{D_g(t)}_{Amenities} \quad \cdot \quad \underbrace{z \cdot \frac{\Gamma_g}{\Gamma_U} \cdot \Big(\pi_{gg}(t)\Big)^{\frac{\alpha}{1-\sigma}} \cdot \Big(M_g(t)\Big)^{\frac{\alpha}{\varepsilon-1}} \cdot \Big(L_g(t)\Big)^{-\theta(1-\alpha)}}_{Real\ Wage} \tag{15}$$

where $\Gamma_U = (\frac{\varepsilon}{\varepsilon-1})^{\alpha}((1-\alpha)\theta)^{\theta(1-\alpha)}$ and $\Gamma_g = A_g^{\alpha}T_g^{\theta(1-\alpha)}$. Note the real wage is a function of the mass of firms and total efficiency units in the regional market, as well as those in other localities through the own trade share $\pi_{gg}(t)$.

4.3 Dynamic Equilibrium and BGP

Now that we defined a static equilibrium for every t we can study the dynamics of the model, which involves spatial labor reallocation through migration as well as the evolution of the mass of firms within each region.

The following Hamilton-Jacobi-Bellman (HJB) equation summarizes the household's recursive problem (I derive this equation in Appendix A.2.1):

$$(\delta+\rho)V_g(z,t) \quad = \quad U_g(z,t)+\dot{V}_g+\lambda\sum_i m_{gi}(z,t)\Big[\delta_{gi}(z,t)V_i(z,t)-V_g(z,t)\Big] \tag{16}$$

where $\delta_{gi}(z,t)=\frac{1}{G}\cdot\kappa_{gi}\cdot m_{gi}(z,t)^{-(\frac{1}{\nu}+1)}$ and the migration shares are given by:

$$m_{gd}(z,t)=\frac{[\kappa_{gd}\cdot V_d(z,t)]^{\nu}}{\sum_i[\kappa_{gi}\cdot V_i(z,t)]^{\nu}} \tag{17}$$

This is the probability that a worker with productivity z moves from region g to d, conditional on having a migration opportunity mediated by λ.

Recall that the distribution of individual productivities $\psi_g(z,t)$ will determine regional labor and population. Thus the evolution of these variables will depend on the Kolmogorov forward equation below (see Appendix A.2.2 for a derivation):

$$\begin{aligned}\dot{\psi}_g(z,t) \quad &= \quad b_g(t)\cdot\frac{N_g(t)}{N(t)}\cdot f(z)-\delta\psi_g(z,t)\\ &- \quad \lambda\Big[(1-m_{gg}(z,t))\psi_g(z,t)-\textstyle\sum_{i\neq g}m_{ig}(z,t)\psi_i(z,t)\Big] \qquad (18)\\ &- \quad \psi_g(z,t)\frac{\dot{N}(t)}{N(t)}\end{aligned}$$

Finally, equation (11) establishes a relation between the fixed cost, labor demand and the mass of firms. Namely, regions with a lower $F_g(t)$ will have a smaller individual labor requirement for each producer which tends to reduce total demand $L^y_g(t)$ in that market. Although this cost is fixed at any point t, equation (9) states its evolution will depend on that of the mass of firms $M_g(t)$. By combining both I obtain:

$$\dot{M}_g(t)=\left(\frac{\alpha+\theta(1-\alpha)}{\varepsilon}\right)L_g(t)M_g(t)^{\eta} \tag{19}$$

This differential equation determines how the regional mass of firms changes over time. I can now define a dynamic equilibrium.

Definition 2. *A* ***dynamic equilibrium*** *is i) a value function $V_g(z,t)$, ii) a distribution $\psi_g(z,t)$ and iii) migration shares $m_{gd}(z,t)$ for $g,d\in G$, $z\in\Omega_z$ and $t\in\mathbb{R}_+$, as well as iv) functions for labor, population and mass of firms $\{L,N,M\}$ and v) wages $\{W\}$ such that:*

1. *M evolves according to equation (19);*

2. *V and m solve the HJB equation in (16), taking $\{L, N, M\}$ and $\{W\}$ as given;*

3. *the densities ψ evolve according to the Kolmogorov equation (18) $\forall r, g \in G$, taking migration decisions as given;*

4. *given ψ, populations and total skills satisfy the following equations:*

$$N_g(t) = N(t) \cdot \int_{\Omega_z} \psi_g(z,t)dz \qquad L_g(t) = N(t) \cdot \int_{\Omega_z} z \cdot \psi_g(z,t)dz \qquad N(t) = \sum_{g \in G} N_g(t)$$

5. *the resulting prices and allocations constitute a static equilibrium $\forall t \in \mathbb{R}_+$.*

Balanced Growth Path A balanced growth path (BGP) is a special type of dynamic equilibrium where all variables grow at a constant rate. To define such a solution, I detrend each variable $x(t)$ by rewriting it relative to its long-run growth rate along the BGP $x(t) = \tilde{x}(t) \cdot e^{\gamma_x t}$. For all derivations see Appendix A.2.3. The result is a set of detrended equilibrium conditions.

The first is a differential equation describing the evolution of regional varieties: the detrended version of equation (19) in terms of growth rates. That is

$$\gamma_{\tilde{M}_g}(t) + \gamma_M = \left(\frac{\alpha + \theta(1-\alpha)}{\varepsilon} \right) \tilde{L}_g(t) \tilde{M}_g(t)^{\eta - 1}. \tag{20}$$

From this equation I also find $\gamma_L = \gamma_M(1-\eta)$, thereby connecting the growth rate of $M_g(t)$ and that of $L_g(t)$ along the BGP. I also detrend the HJB in equation (16) to obtain:

$$\begin{aligned} (\delta + \rho - \gamma_v)\tilde{V}_g(z,t) &= \tilde{U}_g(z,t) + \partial_t \tilde{V}_g(z,t) \\ &+ \lambda \textstyle\sum_i m_{gi}(z,t) \Big[\delta_{gi}(z,t) \tilde{V}_i(z,t) - \tilde{V}_g(z,t) \Big], \end{aligned} \tag{21}$$

where the effective discount rate is now $(\delta + \rho - \gamma_v)$ with $\gamma_v = (\frac{\alpha}{\varepsilon - 1} - (1-\eta)(\phi + \theta(1-\alpha)))\gamma_M$.

The detrended Kolmogorov forward equation (18) is now:

$$\begin{aligned} \partial_t \tilde{\psi}_g(z,t) &= b_g(t) \frac{\tilde{N}_g(t)}{\tilde{N}(t)} f(z) - \delta \tilde{\psi}_g(z,t) \\ &- \lambda \Big[(1 - m_{gg}(z,t)) \tilde{\psi}_g(z,t) - \textstyle\sum_{i \neq g} m_{ig}(z,t) \tilde{\psi}_i(z,t) \Big] \\ &- \Big(\tilde{\gamma}_N(t) + \gamma_N \Big) \tilde{\psi}_g(z,t). \end{aligned} \tag{22}$$

By detrending this equation I find $\gamma_\psi = 0$, which implies from the definition of $L_g(t)$, that labor grows at the same rate as population along the BGP so that $\gamma_L = \gamma_N$. The detrended versions of these variables are are defined by

$$\tilde{N}_g(t) = \tilde{N}(t) \int_{z \in \Omega_z} \tilde{\psi}_g(z,t) dz \qquad \& \qquad \tilde{L}_g(t) = \tilde{N}(t) \int_{z \in \Omega_z} z \tilde{\psi}_g(z,t) dz.$$

Using population dynamics, I compute the growth rate of $\tilde{N}_g(t)$ as a function of regional birth rates and δ:

$$\frac{\dot{\tilde{N}}(t)}{\tilde{N}(t)} = \frac{\sum_g b_g(t) \cdot \tilde{N}_g(t)}{\tilde{N}(t)} - \delta - \gamma_N \tag{23}$$

Note that once the overall economy reaches the BGP, all detrended variables $\tilde{x}(t)$ are constant so that $\tilde{x}(t) = \bar{x}\ \forall t$. I now formally define this type of equilbrium below.

Definition 3. *A **balanced growth path** is a dynamic equilibrium in which population $N_g(t)$ grows at a constant rate γ_N across locations, with constant growth rates for all equilibrium variables and detrended functions $\{\tilde{V}, m, \tilde{\psi}\}$ such that:*

$$\begin{aligned} V_g(z,t) &= e^{\gamma_v t} \bar{V}_g(z) \\ m_{ig}(z,t) &= \bar{m}_{ig}(z) \\ \psi_g(z,t) &= \bar{\psi}_g(z) \end{aligned}$$

where $\{V, m, \psi\}$ solve the dynamic equilibrium, $\{\bar{V}, \bar{m}, \bar{\psi}\}$ are the detrended value function, migration shares and skill distributions at the BGP, $\gamma_v = (\frac{\alpha}{\varepsilon-1} - (1-\eta)(\phi + \theta(1-\alpha)))\gamma_M$ and $\gamma_N = \gamma_M(1-\eta)$.

Along the BGP, the detrended HJB (21) becomes:

$$(\delta + \rho - \gamma_v)\bar{V}_g(z) = \bar{U}_g(z) + \lambda \sum_i \bar{m}_{gi}(z) \left[\bar{\delta}_{gi}(z) \bar{V}_i(z) - \bar{V}_g(z) \right] \tag{24}$$

whereas the Kolmogorov equation (22) is now

$$0 = \bar{b}_g \frac{\bar{N}_g}{\bar{N}} f(z) - (\delta + \gamma_N)\bar{\psi}_g(z) - \lambda(1 - \bar{m}_{gg}(z))\bar{\psi}_g(z) + \lambda \sum_{i \neq g} \bar{m}_{ig}(z) \bar{\psi}_i(z) \tag{25}$$

Finally, to find the population growth rate γ_N, I use the fact that $\dot{\tilde{N}} = 0$ along the BGP in equation 23. This implies:

$$\gamma_N = \frac{\sum_g \bar{b}_g}{\bar{N}} - \delta \tag{26}$$

Note that I could also derive this by integrating the BGP Kolmogorov equation (25) over all z and summing over g, as well as using the fact that along the BGP there is no net migration.

4.4 Model Solution

To compute the solution of this model, I adapt the algorithms in Achdou et al. (2022). This was done in a spatial setting in Crews (2023) to compute the steady state for a centralized economy. However, since an estimation of the structural parameters through impulse response matching requires a simulation of dynamic outcomes, I implement a fixed-point procedure that solves the transition path of the economy as well as a BGP algorithm. To simplify notation I group all general parameters into $\mathbf{\Theta}$ and regional fundamentals into $\mathbf{\Theta}_G$.

Algorithm 1: Balanced Growth Path

Data: parameters $\{\mathbf{\Theta}, \mathbf{\Theta}_G\}$; productivity distribution $f(z)$
Result: solution functions $\{\bar{V}, \bar{\psi}, \bar{m}\}$
Initialize $\{\boldsymbol{W}^0, \boldsymbol{L}^0, \boldsymbol{N}^0\}$;
while *not converged* **do**
  Use $\{\boldsymbol{W}^n, \boldsymbol{L}^n, \boldsymbol{N}^n\}$ to compute shares π^n_{gd} and flow utility $\bar{U}^n_g(z)$;
  Solve the HJB in equation (24). Recover migration shares $\bar{m}^n_{gd}(z)$;
  Use $\bar{m}^n_{gd}(z)$ to solve the Kolmogorov forward equation (25). Recover the distribution $\bar{\psi}^n_g(z)$;
  Use $\bar{\psi}^n_g(z)$ to compute labor supply and population:

$$\hat{L}^n_g = N \cdot \int_{\Omega_z} z\bar{\psi}^n_g(z)dz \qquad \hat{N}^n_g = N \cdot \int_{\Omega_z} \bar{\psi}^n_g(z)dz$$

  then use $\{\hat{\boldsymbol{L}}^n\}$ to compute the wages that satisfy:

$$\hat{W}^n_g \hat{L}^n_g = \sum_d \pi^n_{gd} \hat{W}^n_d \hat{L}^n_d$$

  this is the trade balance in equation (12) ;
  if $\{\boldsymbol{W}^n, \boldsymbol{L}^n, \boldsymbol{N}^n\}$ *close to* $\{\hat{\boldsymbol{W}}^n, \hat{\boldsymbol{L}}^n, \hat{\boldsymbol{N}}^n\}$ **then**
    converged;
  else
    compute $\{\boldsymbol{W}^{n+1}, \boldsymbol{L}^{n+1}, \boldsymbol{N}^{n+1}\}$ as linear combination of old and new values;
  end
end

Algorithm 2: Transition Dynamics

Data: endpoint solutions $\{\bar{V}^1, \bar{\psi}^1, \bar{m}^1\}$ and $\{\bar{V}^2, \bar{\psi}^2, \bar{m}^2\}$; parameter series $\{\boldsymbol{\Theta}(t), \boldsymbol{\Theta}_G(t)\}$; productivity distribution $f(z)$

Result: solution functions $\{\tilde{V}(t), \tilde{\psi}(t), m(t)\}$

Initialize $\{\boldsymbol{W}^0(t), \boldsymbol{L}^0(t), \boldsymbol{N}^0(t)\}$;

while *not converged* **do**

Use $\{\boldsymbol{N}^j(t)\}$ to compute total population $\hat{N}^j(t)$;

Use $\{\boldsymbol{L}^j(t)\}$ to compute a transition path $\{\hat{\boldsymbol{M}}^j(t)\}$ according to equation (20) using the initial condition from the first endpoint;

Use $\{\boldsymbol{W}^j(t), \boldsymbol{L}^j(t), \boldsymbol{N}^j(t)\}$ and $\{\hat{\boldsymbol{M}}^j(t)\}$ to compute shares $\pi^j_{gd}(t)$ and flow utility $\tilde{U}^j_g(t)$;

Solve the HJB equation (21) by iterating backwards from $\bar{V}^2$. Recover migration shares $m^j_{gd}(z,t)$;

Use $m^j_{gd}(z,t)$ to solve the Kolmogorov forward equation (22) by iterating forward from $\bar{\psi}^1$. Recover $\psi^j_g(z,t)$;

Use $\tilde{\psi}^j_g(z,t)$ to compute labor supply and population for each t:

$$\hat{L}^j_g(t) = \hat{N}^j(t) \cdot \int_{\Omega_z} z \cdot \tilde{\psi}^j_g(z,t)dz \qquad \hat{N}^n_g = \hat{N}^j(t) \cdot \int_{\Omega_z} \tilde{\psi}^n_g(z,t)dz$$

then use $\{\hat{\boldsymbol{L}}^j(t)\}$ to compute wages that satisfy:

$$\hat{W}^j_g(t)\hat{L}^n_g(t) = \sum_d \pi^j_{gd}\hat{W}^j_d(t)\hat{L}^j_d(t)$$

this is the detrended trade balance equation.;

if $\{\boldsymbol{W}^j(t), \boldsymbol{L}^j(t), \boldsymbol{N}^j(t)\}$ *close to* $\{\hat{\boldsymbol{W}}^j(t), \hat{\boldsymbol{L}}^j(t), \hat{\boldsymbol{N}}^j(t)\}$ **then**

converged;

else

compute $\{\boldsymbol{W}^{j+1}(t), \boldsymbol{L}^{j+1}(t), \boldsymbol{N}^{j+1}(t)\}$ as linear combination of old and new values;

end

end

5 Structural Estimation

With the framework in the previous section I can study the effects of local migration and reallocation shocks on aggregate outcomes such as output and productivity. To carry this out, I first estimate the structural parameters so that the model is consistent with the impulse responses in Section 3.

5.1 Estimation Strategy

The model parametrization includes a tuple of regional fundamentals $\{T_g, A_g, D_g\}$ as well as 14 structural parameters: those I set exogenously $\mathbf{\Theta}_1 = \{\alpha, \rho, \sigma, \zeta_\tau, \gamma_L, \bar{N}\}$ and those I estimate within the simulation

$$\mathbf{\Theta}_2 = \{\varepsilon, \eta, \nu, \phi, \zeta_m, \theta, \lambda, \delta\}.$$

Given a set of parameters I compute the initial and final steady states, as well as the transition path that results from an exogenous series of regional birth rates $\{b_g(t)\}$ that take the economy away from the first BGP. This produces a simulated dataset I then use to replicate the shift-share IV and estimate the SVAR-IV described in Section 2.

Clustering Commuting Zones Solving the theoretical model is time-consuming and the cost increases dramatically with the number of regions. Therefore I need to reduce this set from the 660 CZs used in the empirical part to estimate the structural parameters of the theory. To carry this out, I applied a K-means clustering procedure based on geographical coordinates and the variables in the VAR.

In particular, for a given number of clusters, I use the dataset with all CZs in 2010 and perform a K-means clustering algorithm where the "features" are the variables in the empirical VAR as well as the CZ coordinates. This produces a set of clusters containing CZs that are similar in terms of migration, output and other economic variables, but that are also geographically close to each other. This rules out, for example, a cluster with some CZs in California as well as Florida. I then aggregate the VAR variables at the cluster level and re-estimate the SVAR-IV to compare the IRF coefficients with the ones in Section 3. I repeat these steps for a number of clusters ranging from 15 to 100, and choose the grouping that produces the coefficients closest to the ones in the baseline estimation. The result is set of 35 CZ-clusters.

Exogenous Parameters I set $\rho = 0.1$ as in Crews (2023) and $\sigma = 2$ following the results in Boehm, Levchenko and Pandalai-Nayar (2023). I target the average share of personal consumption expenditures on housing over the time period and set $\alpha = 0.89$. For the initial distribution of productivities $f(z)$, I use a truncated $Lognormal(\mu_f, \sigma_f)$ distribution using the estimates of the mean and coefficient of variation from Huggett, Ventura and Yaron (2006) to set μ_f and σ_f. To identify available land for housing T_g, I use raster data from the USGS National Land Cover as well as Data Elevation Models. Specifically, for each county I find the area (in square miles) that does not contain open water, wetlands or perennial snow as well as with an inclination lower than 15% following architectural guidelines and Saiz (2010).

I follow Peters (2022) parameterize bilateral trade and migration costs as functions of distance by setting $\tau_{gd} = (d_{gd}/d_{min})^{\zeta_\tau}$ and $\kappa_{gd} = (d_{gd}/d_{min})^{\zeta_m}$, with $d_{gg} = d_{min}$. Since CZ group one or more counties, I can compute the average distance between them. Therefore I use the 5% quintile of these within-CZ average distances to set $d_{min} = 32$mi. Although I estimate ζ_m through impulse response matching, I estimate ζ_τ by regressing bilateral prices on distance, similar to Castro-Vincenzi et al. (2024).

In particular, I use the Commodity Flow Survey (CFS) datasets from 2012 and 2017, which provide information on domestic freight shipping within the US. For each shipment i, I observe its weight and value, as well as the great circle distance $d_{i,t}$ between shipment origin and destination. Thus, since in the model $p_{gd}(t) \propto \tau_{gd}$, I estimate the following regression:

$$\log p_{i,t} = \beta_0^p + \zeta_\tau \log(d_{i,t}) + \boldsymbol{X}_{i,t} + \epsilon_{i,t} \tag{27}$$

where $p_{i,m,n,t}$ is the value per pound of the shipment and $\boldsymbol{X}_{i,t}$ are a set of controls such as destination, origin and quarter fixed effects. The estimates are reported in Table 5 in the Appendix and I use the estimate in the column (4).

Finally, I assume the economy is at a BGP in 2002 and set γ_L to 1.25% by targeting the average growth rate of the civilian labor force in the 10 years preceding my sample. For total population I use the sum of wage employment in that year from the sample in Section 2 so that $\bar{N} \approx 134$ mil. workers.

Internal Estimation For a given set $\boldsymbol{\Theta}_2$, I estimate the remaining regional fundamentals $\{A_g, D_g\}$ by targeting output per worker and population shares in 2002 while solving the initial steady state. I use a modified version of Algorithm 1 where I solve for the fixed point of parameters in addition to endogenous variables. This also allows me to find λ and δ. I impute the latter by using equation 26 and the birth rates $\bar{b}_g^1$ observed 25 years before the first year in my sample. These are the initial elements in the series $\{b_g(t)\}$ I will use to simulate the transition. On the other hand, to infer the probability of migration opportunities I target the sum of migration inflows into all regions:

$$\underbrace{\frac{\sum_g \bar{m}_g}{\bar{N}}}_{Observed} = \lambda \cdot \underbrace{\sum_g \int \sum_{i \neq g} \bar{m}_{ig}(z) \cdot \bar{\psi}_i(z) dz}_{Model\ Variable} \tag{28}$$

Once this is complete, I compute the second endpoint for the transition: the final BGP. In terms of parameters, the only difference with the initial steady state is that I use the lagged birth rates corresponding to the last year of my sample $\bar{b}_g^2$.

With both endpoints in hand, I can now use Algorithm 2 to compute the transition dynamics of the economy. In particular, I leave all parameters constant except birth rates $\{b_g(t)\}$, which are the same as the ones I use to build the shift-share instrument. This results in a panel series of 17 years (including the first and last that I use for the BGP computation). Note it is unlikely the economy reaches the second steady state after this period. Therefore, I assume $b_g(t) = \bar{b}_g^2$ for all t thereafter and set the total periods to a higher number ($T = 200$).

To estimate $\mathbf{\Theta}_2$, I follow an impulse response matching procedure. Specifically, I repeat the internal estimation steps described above for a sequence of parameters in a Sobol grid and seek to minimize the following objective function:

$$J = \min_{\mathbf{\Theta}_2} (\hat{\mathbf{\Gamma}} - \mathbf{\Gamma}(\mathbf{\Theta}_2))' W^{-1} (\hat{\mathbf{\Gamma}} - \mathbf{\Gamma}(\mathbf{\Theta}_2)) \tag{29}$$

where $\hat{\mathbf{\Gamma}}$ is a vector with the IRFs estimated using the 35 clusters, $\mathbf{\Gamma}(\mathbf{\Theta}_2)$ are the model generated IRFs. The weighting matrix W^{-1} is diagonal and contains the reciprocals of coefficient variance, similar to Christiano, Eichenbaum and Evans (2005).

5.2 Parameter Estimates

The results from the impulse response matching are displayed in Table 4 and Figure 7 shows the model fit.

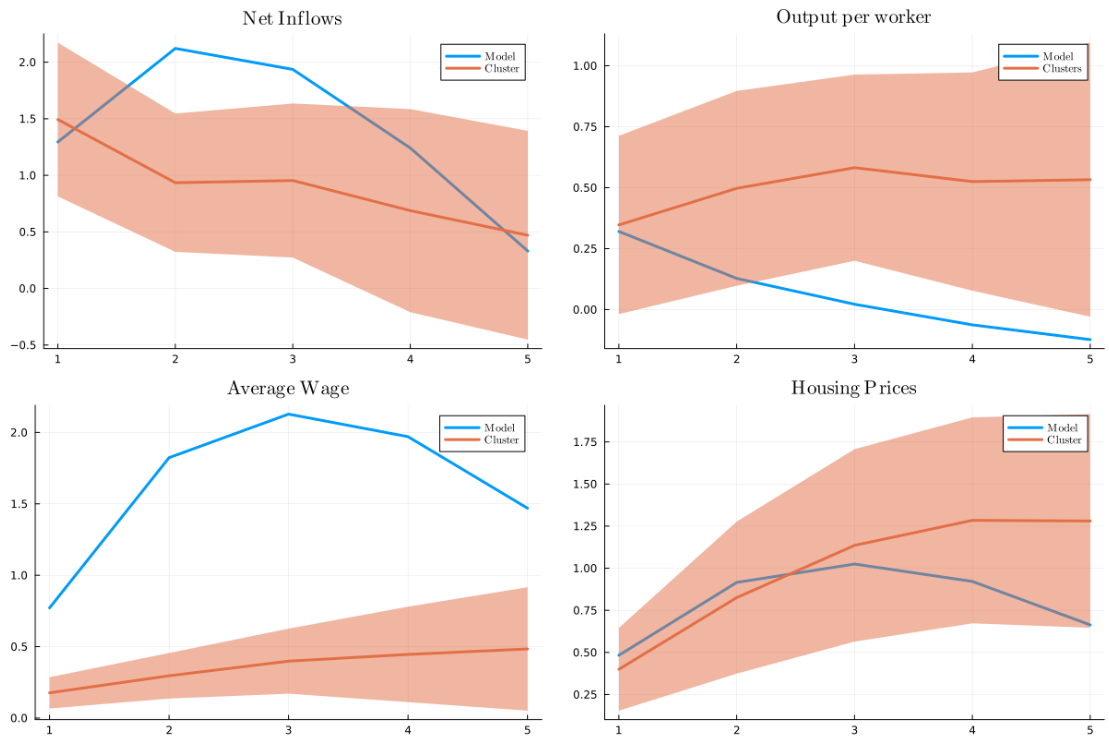
TABLE 4 STRUCTURAL PARAMETERS

Parameter	Interpretation	Estimate
ε	*Elasticity of substitution*	5.15
η	*Inter-temporal elasticity*	0.85
ν	*Migration elasticity*	0.95
ϕ	*Elasticity of amenities*	1.12
ζ_m	*Elasticity of migration costs*	3.39
θ	*Share of land in housing*	0.82

6 Population and Reallocation Shocks

How would aggregate output per worker respond over time if some regions lost a share of their workers? Although the IRFs in Section 3 show what the effect of migration on local conditions is, they are not enough to infer the relevance of population flows on aggregate

Figure 7. Model Fit



Note: The red line represents the cumulative impulse response (CIRF) estimated from the 35 K-means clusters. The red shade indicates a 90% confidence level. Standard errors are generated by Monte-Carlo with 200 repetitions. The blue line is the CIRF estimated by simulating the model with the baseline parametrization obtained from indirect inference.

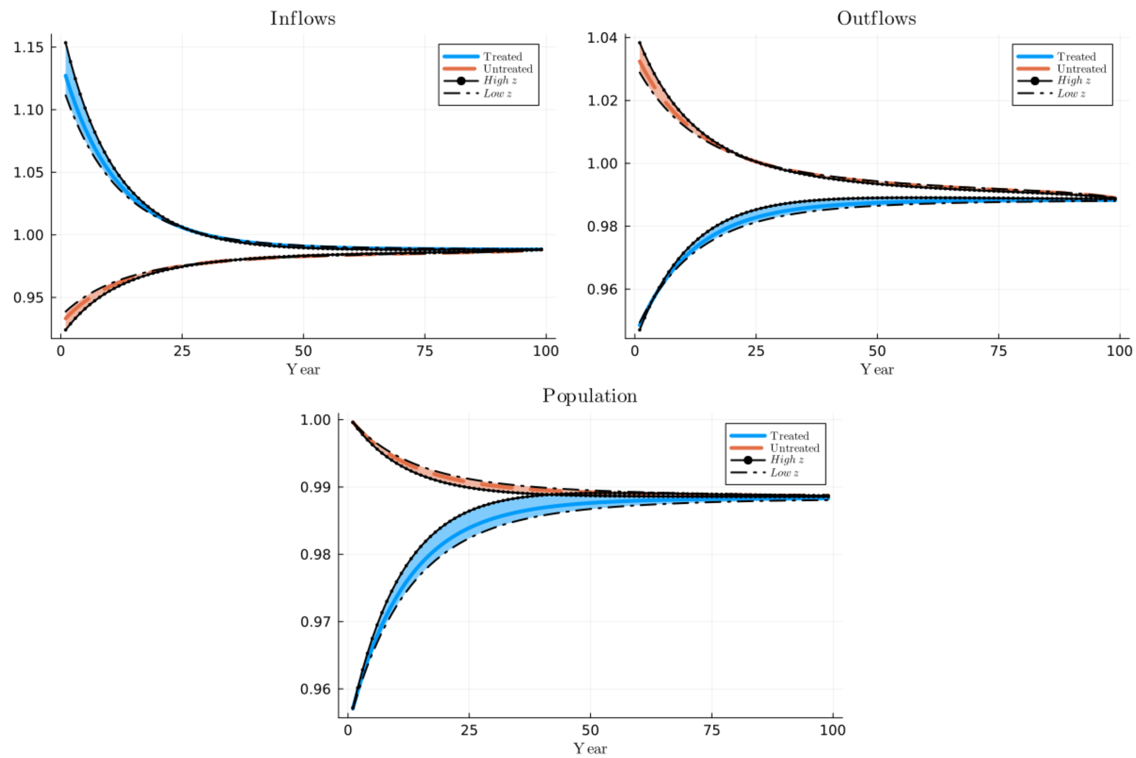
variables. Therefore, to answer this question, I use the calibrated model. Specifically, I consider two policy exercises separately. The first one decreases the total number of workers in the economy by reducing the population in certain areas while keeping the size of the remaining regions constant. I call this a "reduction" shock. The second one is a "reallocation" shock: instead of maintaining the population of other locations, I increase by a uniform share so as to keep the total number of households constant.

An important element of these counterfactuals is that the local population share that is removed or relocated differs across treated regions so that these local shocks are a geographically heterogeneous. To calibrate these shares I use the estimates from Passel and Krogstad (2023) to identify the states with the highest number of undocumented immigrants. I then match these with one of the 35 clusters in my model and perform the counterfactuals. Consequently, we can think of the first shock as a general deportation of approximately 1% of the labor force. By region however, this percentage varies from $x\%$ to $x\%$. On the other hand, in the second exercise these workers are redistributed to places with a lower incidence of undocumented immigration, in a similar manner to the transportation of migrants to sanctuary cities by some states in 2023 (see for example Goodman et al. (2024)).

6.1 Reducing Local Population

When workers are deported and removed from the economy, people from untreated areas start migrating to treated regions as shown in Figure 11. The reason behind these flows is that, immediately after the shock, housing prices decrease and congestion externalities produce higher amenities. Therefore, the higher attractiveness of these markets, relative to the rest of the US, draws people in. Thus inflows increase, outflows fall and local population starts to increase after the initial drop. However, local populations converge to a new steady state level that is 1% lower than the one before the policy takes place.

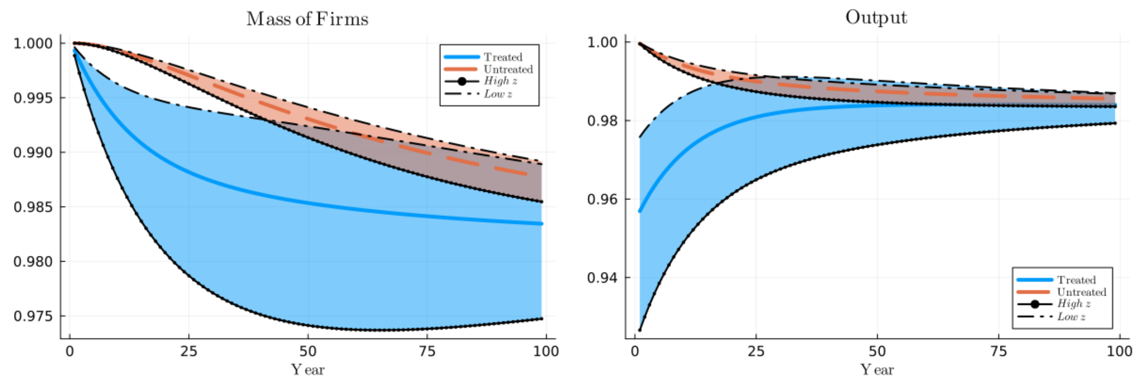
Figure 8. Reduction Shock: Regional Population Flows



Although the number of varieties is initially the same in affected regions, the lower labor supply implies fewer firms are able to pay the fixed cost. In addition to this, $M_g(t)$ has a dynamic effect on this cost through equation (9). Both mechanisms lead to a steady decline in the mass of firms as shown in Figure 9. The same process occurs in the remaining areas since they lose population through migration outflows as we saw above. Eventually, the response of labor and varieties decrease output in untreated locations whereas it increases for shocked markets. Nevertheless, both converge to a level that is around 2.5% lower than the initial steady state.

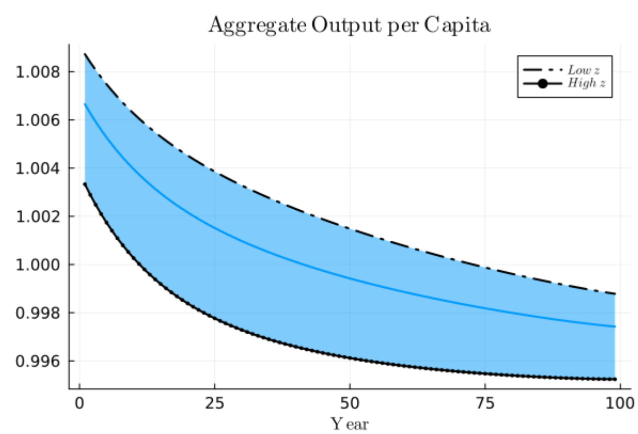
In terms of aggregate effects, the deportation shock leads to a long run drop in output per worker larger than 1.5% shown in Figure 10. As we will see in the next counterfactual,

Figure 9. Population Shock: Regional Output



this new steady state is solely due to the fact that workers exit local economies without being replaced elsewhere. Therefore the overall economy is left with a smaller labor supply and consequently fewer varieties, which reduces productivity. Note this is similar to an inverse version of the refugee allocation in Peters (2022) where output per worker also increases in the long run. However, here the effect comes from aglomeration externalities in all markets and not just in the manufacturing sector.

Figure 10. Population Shock: Aggregate Output



6.2 Reallocating Workers

How would aggregate productivity react if instead of removing workers they were reallocated to other sectors? Effectively, this policy also takes the economy out of its initial steady state but does not change the BGP towards which the economy transitions to in the long-run. Figure 11 shows that, similar to before, regions that lose their population see an increase of net inflows whereas the opposite is true of areas that receive the initial influx. Right after the shock, congested amenities and higher housing prices drive migrants back to areas whose population was relocated. This dynamic continues for 50 years until the number of workers in each places converges back.

The mass of firms in each region also transition back to the initial steady state, as well as output. However, unlike population, these variables take longer to converge. The number of producers is a slow moving variable that follows the differential equation 20. It therefore takes time to adjust, which is why the initial drop in shocked areas also occurs in a longer time frame relative to labor.

Figure 11. Reallocation Shock: Regional Population Flows

images/5_Counterfactuals/Reallocation/irf_cluster_baseline_inflows.png

images/5_Counterfactuals/Reallocation/irf_cluster_bas

images/5_Counterfactuals/Reallocation/irf_cluster_baseline_population.pn

Figure 12. Population Shock: Regional Output

images/5_Counterfactuals/Reallocation/ ... /irf_cluster_bas

Figure 13. Population Shock: Aggregate Output

images/5_Counterfactuals/Reallocation/irf_cluster_basel

7 Conclusion

This paper studies the dynamic effect of increasing population inflows on local markets. Most of the previous research on labor mobility and its impact on economic outcomes focused on either short or long-term responses, but did not consider transitional dynamics. Although some papers address this element, their identification of structural migration shocks relies on timing assumptions, whereas the analysis above adopts an SVAR-IV approach using instruments based on weather variations. The results reveal labor productivity, wages and employment opportunities in urban economies respond positively to a 1% increase in population inflows.

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