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The Contribution of Immigration to Local Labor Market Adjustment

Michael Amior

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Economic and Social Research Council

Abstract
The US suffers from persistent regional disparities in employment rates. In principle, these disparities should be eliminated by population mobility. Can immigration fulfill this role? Remarkably, since 1960, I show that new migrants from abroad account for 40% of the average population response to these disparities - which vastly exceeds their historic share of gross migratory flows. But despite this, immigration does not significantly accelerate local population adjustment (or reduce local employment rate disparities), as it crowds out the contribution from internal mobility. Indeed, this crowd-out can help account for the concurrent decline in internal mobility. Finally, I attribute the "excess" foreign contribution to a local snowballing effect, driven by persistent local shocks and the dynamics of migrant enclaves. This mechanism raises challenges to the (pervasive) application of migrant enclaves as an instrument for foreign inflows. But rather than abandoning the instrument, I offer an empirical strategy (motivated by my model) to overcome these challenges; and I demonstrate its efficacy.

Key words: Immigration, geographical mobility, local labor markets, employment
JEL Codes: J61; J64; R23

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Michael Amior, Hebrew University of Jerusalem and Centre for Economic Performance, London School of Economics.

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1 Introduction

The US suffers from large regional disparities in employment-population ratios ("employment rates") which have persisted for many decades (Amior and Manning, 2018). These inequities have been exacerbated by the collapse of manufacturing employment (Charles, Hurst and Notowidigdo, 2016), whose impact is heavily concentrated geographically (Autor, Dorn and Hanson, 2013). In principle, these disparities should be eliminated by regional mobility, as in Blanchard and Katz (1992). But given strong local persistence in labor demand shocks, even a large population response is insufficient (Amior and Manning, 2018). And troublingly, as Panel A of Figure 1 shows, regional mobility (the solid line) has declined markedly in recent decades (Molloy, Smith and Wozniak, 2011).

In the face of these challenges, Borjas (2001) famously argues that new (footloose) immigrants can "grease the wheels" of the labor market: that is, they accelerate the adjustment of local population.[1] But though the rate of immigration has grown rapidly since the 1960s, just 17% of migratory flows to US states originate from abroad (Panel B). Given this, can immigration make a substantive difference to local disparities? One might focus on immigrants' contribution to *internal* mobility after arrival: they do initially make more cross-state moves than natives, but this gap largely disappears after five years in the US (see Appendix D). Alternatively, foreign-born residents may contribute to local adjustment through selective emigration: Cadena and Kovak (2016) find this is an important mechanism during the Great Recession, though the effect is confined to low educated Mexicans. But either way, despite the large expansion of immigration in recent decades, Dao, Furceri and Loungani (2017) and Amior and Manning (2018) find no evidence of speedier adjustment of local labor markets.

In this paper, I attempt to resolve these puzzles and study the broader implications. I make four contributions. (1) I quantify the foreign contribution to population adjustment across 722 commuting zones (CZs) over 50 years of US history. Remarkably, new immigrants *alone* account for 40% of the average population response to local employment shocks. This vastly exceeds their share of gross migratory flows over the same period, which is about 10%.[2] Unlike in Cadena and Kovak (2016), longer-term immigrants con-

[1]Card and Lewis (2007), Jaeger (2007), Kerr (2010), Cadena (2013, 2014), Beerli, Indergand and Kunz (2017), Albert and Monras (2018) and Basso, D'Amuri and Peri (2019) confirm that new migrants' location decisions respond strongly to local economic conditions. Basso, Peri and Rahman (2017) extend the hypothesis of "greasing the wheels" beyond geography: immigration attenuates the impact of technical change on local skill differentials. And the hypothesis is not only limited to immigration: Dustmann, Schoenberg and Stuhler (2017) find that older workers (who supply labor elastically) protect the employment of younger workers (who supply labor inelastically) in the event of adverse shocks.

[2]The mean share of gross annual flows to US states over 1964-2010 is 12%: see Panel of B of Figure 1. But the share for CZs will be smaller, because there is more mobility across CZs than states. See Section 3.2 for further discussion.

tribute little (whether through internal mobility or selective emigration); and the effects are also very general: I estimate large contributions across education groups, and from immigrants of diverse origins. (2) Unlike Borjas (2001), I argue this is entirely unconnected with any mobility advantages of immigrants. Rather, it is driven by their strong preference to settle in migrant enclaves, which are disproportionately located in high-employment areas. I attribute this spatial correlation to a local snowballing effect, driven by persistent local shocks and the dynamics of migrant enclaves. I confirm the quantitative importance of this mechanism through calibration. (3) Despite this, I show that new foreign arrivals do not significantly accelerate local population adjustment (or reduce local employment rate disparities), as they crowd out the contribution from *internal* mobility. I show this effect is too large to be driven by the labor market alone. (4) Finally, my results indicate that instrumenting foreign inflows with local migrant enclaves (as is common in the literature) will likely violate the exclusion restriction, given the enclaves' spatial correlation with persistent labor demand shocks. However, I offer an empirical strategy (motivated by my model) to overcome both this challenge and that of serially correlated foreign inflows (as in Jaeger, Ruist and Stuhler, 2018); and I demonstrate its efficacy.

How do these results affect the interpretation of Figure 1? Though gross migratory flows have declined on aggregate, this need not imply more sluggish local adjustment: this is because the flows of new immigrants (which have expanded markedly) are more strongly directed to high-employment areas. Moreover, the acceleration of immigration likely *contributed* to the decline in regional mobility: based on my estimates of crowd-out, increases in foreign inflows since 1960 will have caused a 40% decline (all else equal) in the internal response to employment shocks. This insight casts a more positive light on the phenomenon: the vast foreign contribution to local adjustment saves US residents from having to make (potentially costly) long-distance moves themselves. And it raises concerns about policies, common in Europe, which restrict asylum seekers' choice of residence.

Beyond studying the implications for regional mobility, a key innovation here is to account for local labor market dynamics. Amior and Manning (2018) show these dynamics are crucial to understanding the contribution of *internal* mobility to local labor market adjustment, even over decadal census intervals. I argue here they are also indispensable for an analysis of the *foreign* contribution, both for understanding (theoretically) its origin and identifying (empirically) its impact. Indeed, I show in Appendix H that accounting for dynamics in Cadena and Kovak's data can help reconcile our findings.

My model of local adjustment extends that of Amior and Manning (2018). Workers move to higher-utility areas, but this process takes time; and new to this paper, I distinguish between the contributions of foreign and internal migration. This yields an "error correction" empirical specification, where decadal changes in log population depend on contemporaneous changes in log employment and the initial log employment rate (the local deviation from steady-state). The employment rate can serve as a "sufficient statistic" for local economic opportunity, as an alternative to the more common real consumption wage (which is notoriously difficult to measure for detailed local geographies). In an effort to exclude supply shocks, I instrument the employment change and lagged employment rate with current and lagged Bartik (1991) industry shift-shares.

The model fits the data well: I estimate large but incomplete population adjustment over decadal intervals to local employment shocks. Remarkably, new immigrants (arriving within these intervals) account for 40% this response, and the contribution is even larger among college graduates. The residual effect is almost entirely driven by natives: foreign-born *residents* contribute little to the population response (whether through internal mobility or selective emigration). I show that the "excess" of the 40% foreign contribution (over its 10% share of gross flows) can be explained statistically by spatial correlation between migrant enclaves and local employment conditions. I attribute this correlation to a local snowballing effect, driven by the dynamics of migrant enclaves. Intuitively, new immigrants are drawn to places enjoying positive employment shocks. This causes local enclaves (which follow a unit root) to permanently expand, which attracts further immigrants - given their strong preference to settle in large enclaves. But since the shocks themselves are heavily serially correlated (due in part to secular shifts in industrial composition), this preference for enclaves will amplify the foreign response to *current* shocks. Importantly, a dynamic model (disciplined by the data) can quantitatively account for this effect.

What are the implications for local adjustment? The model shows a larger supply of new immigrants should narrow local utility differentials. But if internal flows are themselves elastic, this will discourage existing residents from themselves relocating - thus "crowding out" their contribution. In the data, I cannot reject perfect crowd-out: population is not significantly more responsive in CZs which are better supplied by new immigrants, as predicted by the enclave shift-share of Altonji and Card (1991) and Card (2001). The larger foreign contribution to adjustment in these areas is almost entirely offset by a reduced contribution from internal mobility - and specifically from natives. Given I am controlling here for dynamics, accounting for local heterogeneity is empirically demanding. But I also derive a more tractable "semi-structural" crowd-out specification, which assumes the enclave shift-share enters the system exclusively through *realized* foreign inflows: the result is the same, but now with remarkable precision.[3] This crowd-out

[3] Since I condition on employment (as directed by my model), this crowd-out effect is not comparable to others in the literature. I choose this approach because I seek to estimate the internal response for a *given* employment shock. In contrast, other papers (most famously, Card, 2001, and Borjas, 2006, and more recently e.g. Dustmann, Schoenberg and Stuhler, 2017, and Monras, forthcoming) seek to estimate the *unconditional* impact of foreign inflows, for which employment may be an important margin of adjustment. I elaborate on this point in Section 2.5. See Amior (2020) for unconditional estimates using identical data and a discussion of the broader literature.

effect is too large to be driven by the labor market alone: the internal response to foreign inflows significantly exceeds its response to employment shocks. Native distaste for migrant enclaves may play a role, as in Card, Dustmann and Preston (2012).

Of course, the dynamics present a formidable challenge to identifying crowd-out and the local impact of immigration more generally. Foreign inflows are traditionally instrumented with historic migrant enclaves, but my results suggest these enclaves cannot credibly exclude demand shocks (confirming the fears of Borjas, 1999). Indeed, it is the very violation of this exclusion restriction which accounts for the excess foreign response. Persistence in the enclave instrument also makes it difficult to disentangle the impact of current and historical foreign inflows (Jaeger, Ruist and Stuhler, 2018). But rather than abandoning the instrument, I offer a strategy to overcome both these challenges. Based on my model, controlling for the lagged employment rate (suitably instrumented) allows me to partial out the entire history of demand and migration shocks. Further exploration of the dynamics (including tests of pre-trends) suggests the employment rate performs this function well. One might alternatively impose heavier structural assumptions (as in Colas, 2018) or exploit natural experiments (e.g. Cohen-Goldner and Paserman, 2011; Edo, forthcoming; Monras, forthcoming), but such experiments restrict analysis to specific historical episodes. In contrast, my approach is applicable to very general settings.

I set out the model in Section 2 and describe the data in Section 3. Section 4 estimates the mean foreign contribution to adjustment, and Section 5 the extent of crowd-out and the implications for internal mobility. In Section 6, I simulate the dynamic response to local employment shocks and quantify the "snowballing" mechanism for the excess foreign contribution. The Appendices contain theoretical extensions and numerous empirical sensitivity tests, as well as a reconciliation with Cadena and Kovak (2016).[4]

2 Model of local population adjustment

2.1 Local equilibrium conditional on population

In line with Amior and Manning (2018), the model has two components: (1) a characterization of local equilibrium conditional on population (based on Roback, 1982) and (2) dynamic equations describing population adjustment. New to this paper, I distinguish

[4]Cadena and Kovak find the (low educated) native population is insensitive to labor demand, which rules out the possibility of large crowd-out. Monras (2015) attributes this result to unobserved divergent trends in local native and Mexican populations. But in Appendix H, I show that by controlling for observable local dynamics (as summarized by the initial employment rate), I identify a large native response in Cadena and Kovak's data. The effect of dynamics is intuitive: as Cadena and Kovak note, those cities which suffered larger downturns during their Great Recession sample had enjoyed larger upturns earlier in the decade; and if adjustment is sluggish, local population movements during the crisis will reflect responses to both. The data reject the hypothesis that these dynamics are unimportant, just as in my 50-year dataset.

between foreign and internal mobility. In what follows, I derive empirical specifications for the crowding out effect (both "reduced form" and more tractable "semi-structural" versions), and I study the determinants of the foreign contribution to adjustment.

To simplify the theoretical exposition, I will assume that native and migrant labor are identical and perfect substitutes in production. This can be motivated by the existing literature, which typically finds they are close substitutes.[5] To the extent this is false, the model will overstate any impact of immigration on native outcomes. But I do *not* exclude a role for imperfect substitutability in my empirical specifications. Instead, I estimate the relationships described in the model empirically, and I test the validity of the assumptions ex post - in line with the methodology of Beaudry, Green and Sand (2012). As it happens, native and migrant employment rates do respond similarly to both immigration and employment shocks - as these assumptions predict. In a similar spirit, I do not account for skill heterogeneity (see Amior, 2020, for such an extension); but as I explain below, the sufficient statistic result allows me to estimate the model separately by education.

There are two goods: a traded good priced at P everywhere, and a non-traded good (housing) priced at P_r^h in area r. Assuming homothetic preferences, one can derive a unique local price index:

$$P_r = Q\left(P, P_r^h\right) \tag{1}$$

I assume labor supply is somewhat elastic to the real consumption wage:

$$n_r = l_r + \epsilon^s \left(w_r - p_r\right) + z_r^s \tag{2}$$

where lower case denotes logs: n_r is employment, l_r is population, w_r is the nominal wage, and z_r^s is a local supply shifter. Labor demand is given by:

$$n_r = -\epsilon^d \left(w_r - p\right) + z_r^d \tag{3}$$

where z_r^d is a local demand shifter. Using (2) and (3), I can solve for employment in terms of population and local prices. And a specification for housing supply and demand (as in Amior and Manning, 2018) will then be sufficient to solve for all endogenous variables in terms of population alone.

I write indirect utility in terms of the real consumption wage $w_r - p_r$ and the value of local amenities a_r:

$$v_r = w_r - p_r + a_r \tag{4}$$

[5]Within skill cells, Ottaviano and Peri (2012) estimate an elasticity of substitution between natives and migrants of about 20. Card (2009) finds even larger numbers, and Borjas, Grogger and Hanson (2012) and Ruist (2013) are unable to reject perfect substitutability. At the aggregate level (the relevant context here), differences in skill composition will also matter. But in the US, natives and migrants have similar college shares, which is the crucial margin of skill if high school dropouts and graduates are close substitutes (as in e.g. Card, 2009; Ottaviano and Peri, 2012).

Crucially, the real wage can be replaced by labor supply (2). So the employment rate can serve as a sufficient statistic for local labor market conditions, conditional on the supply and amenity effects:

$$v_r = \frac{1}{\epsilon^s} \left(n_r - l_r - z_r^s \right) + a_r \tag{5}$$

In practice, this interpretation of the local employment rate may be compromised by heterogeneous preferences for leisure. But as I argue in Section 3.3, this may be addressed by adjusting employment rates for demographic composition. A related concern is heterogeneous preferences over local consumption (Albert and Monras, 2018), but this should not affect the validity of the sufficient statistic result.[6] Beyond this, Amior and Manning (2018) show the result is robust to numerous model variants: multiple traded and non-traded sectors[7], agglomeration, endogenous amenities and market frictions; and Amior and Manning (2019) show it is robust to cross-area commuting.

2.2 Local dynamics

In the long run, the model is closed by imposing spatial invariance in v_r, as in Roback (1982). This determines steady-state population in each area. But I allow for dynamic adjustment to this state, with population l_r responding sluggishly to local utility differentials. New to this paper, I distinguish between the contributions of internal and foreign migration:

$$dl_r = \lambda_r^I + \lambda_r^F \tag{6}$$

where λ_r^I is the instantaneous rate of net internal inflows (from within the US) to area r, and λ_r^F is the foreign inflow rate, relative to local population. In principle, foreign outflows may also play a role: Akee and Jones (2019) find that immigrants emigrate in response to negative earnings shocks. However, my estimates suggest emigration contributes little to local adjustment to employment shocks, so I have chosen not to account for it here.

Using a logit model of residential choice (as in Monras, 2015, or Diamond, 2016), λ_r^I and λ_r^F can be written as linear functions of utility v_r. As Appendix A shows, the net internal flow λ_r^I is given by:

$$\frac{\lambda_r^I}{\mu^I} = \gamma^I \left(n_r - l_r - z_r^{sa} \right) \tag{7}$$

where $z_r^{sa} \equiv z_r^s - \epsilon^s a_r$ denotes the combined supply and amenity effects; $\gamma^I \geq 0$ is the elasticity of net flows; and μ^I is the (spatially invariant) steady-state rate of internal mobility, i.e. in the absence of local differentials. As I show in Appendix A, the spatial invariance of μ^I can be motivated with a concept of network size: in spatial equilibrium,

[6] Suppose natives and migrants place different weight on local prices. Their labor supplies will then depend on their respective price indices. So, the real consumption wage in both natives' and migrants' utility can still be replaced by the employment rate, at least after adjusting for demographic composition.

[7] Borjas (2013) and Hong and McLaren (2015) emphasize that migrants support local demand through consumption. In my model, this is observationally equivalent to a flatter labor demand curve.

the total inflow to each area r will then be proportional to local population. There is no national intercept in (7), but z_r^{sa} may be redefined to include one. Agents in (7) are implicitly myopic: their behavior depends only on current conditions. But as Amior and Manning (2018) show, one can write an equivalent equation for forward-looking agents, where the elasticity γ^I depends both on workers' mobility and the persistence of shocks.

Turning now to foreign inflows:

$$\frac{\lambda_r^F - \mu_r^F}{\mu_r^F} = \gamma^F \left(n_r - l_r - z_r^{sa}\right) \tag{8}$$

where μ_r^F is the local "foreign intensity", i.e. the foreign inflow in the absence of local differentials. Unlike μ^I, I permit μ_r^F to vary with r: e.g. absorption into the US is facilitated by co-patriot networks (due to language or job market access) whose strength varies regionally. For now, I take μ_r^F as given. But I study its evolution empirically in Section 4: this process is crucial to interpreting the foreign contribution to adjustment.

I assume that, after entry, immigrants behave identically to natives. The intent is merely to simplify the theoretical analysis. I do *not* impose this restriction on the empirical estimates (where I distinguish between the migratory responses of natives and longer-term migrants), but these estimates offer no compelling reason (ex post) to reject it. The assumption can also be motivated ex ante by the evidence in Appendix D: though the newest migrants do make more internal moves than natives, the gap becomes small after five years of entry - and turns negative within ten.

Summing (7) and (8), aggregate population growth is given by:

$$dl_r = \mu_r^F + \gamma_r \left(n_r - l_r - z_r^{sa}\right) \tag{9}$$

where γ_r is the (heterogeneous) aggregate population elasticity in area r:

$$\gamma_r \equiv \gamma^I \mu^I + \gamma^F \mu_r^F \tag{10}$$

2.3 Discrete-time specification

To estimate the population response, I need a discrete-time expression for (9). Assuming the supply/amenity effect z_r^{sa} and employment n_r change at constant rates within discrete intervals, and that foreign intensity μ_r^F is constant within intervals, Appendix B.1 shows:

$$\Delta l_{rt} = \left(\frac{1 - e^{-\gamma_{rt}}}{\gamma_{rt}}\right) \mu_{rt}^F + \left(1 - \frac{1 - e^{-\gamma_{rt}}}{\gamma_{rt}}\right) \left(\Delta n_{rt} - \Delta z_{rt}^{sa}\right) + \left(1 - e^{-\gamma_{rt}}\right) \left(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa}\right) \tag{11}$$

where μ_{rt}^F denotes foreign intensity between $t-1$ and t, and γ_{rt} is the aggregate population elasticity in this interval. (11) is an error correction model (ECM) in population l_{rt}

and employment n_{rt}: population growth Δl_{rt} depends on current Δn_{rt} and the lagged employment rate $(n_{rt-1} - l_{rt-1})$, which accounts for initial conditions. The effect of each expands from 0 to 1 as γ_{rt} increases from 0 to ∞. A coefficient of 1 on Δn_{rt} indicates full population adjustment to contemporaneous shocks, and a coefficient of 1 on $(n_{rt-1} - l_{rt-1})$ indicates that any initial steady-state deviation is eliminated in the subsequent period. Conversely, coefficients closer to zero indicate sluggish adjustment.

Crucially, employment growth and the lagged employment rate fully account for the dynamics of local utility, conditional on the supply/amenity shocks. As a result, the demand shifter z_r^d does *not* appear in this equation; and this makes it easier to identify the impact of immigration. This is true of all the empirical specifications I study, and it motivates an important methodological contribution which I describe below.

2.4 Crowding out effect

Equation (11) conceals the interactions between foreign and internal mobility. In particular, a larger foreign response to employment shocks (elicited by larger foreign intensity, μ_{rt}^F) crowds out the internal response. To see this, notice the coefficients on Δn_{rt} and $(n_{rt-1} - l_{rt-1})$ in (11) are concave in γ_{rt}. As a result, doubling the aggregate elasticity γ_{rt} (by raising μ_{rt}^F in (10)) will not double the discrete-time responses. Intuitively, a larger foreign response makes utility less sensitive to local shocks; and narrower utility differentials discourage existing residents themselves from relocating.

To estimate these crowd-out effects, I linearize the empirical specification. Let $\lambda_{rt}^F \equiv \int_{t-1}^t \lambda_r^F(\tau)\, d\tau$ denote the discrete-time foreign contribution to local population. Using (7), (8) and (11), I show in Appendix B.2 that:

$$\lambda_{rt}^F \approx \mu_{rt}^F + \frac{\gamma^F \mu_{rt}^F}{\gamma^I \mu^I} \left[\left(1 - \frac{1 - e^{-\gamma^I \mu^I}}{\gamma^I \mu^I} \right) (\Delta n_{rt} - \Delta z_{rt}^{sa}) + \left(1 - e^{-\gamma^I \mu^I} \right) (n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa}) \right] \tag{12}$$

after linearizing around $\mu_{rt}^F = 0$. In areas with larger foreign intensity μ_{rt}^F, the foreign contribution λ_{rt}^F is both larger independently of shocks (a "direct" effect of μ_{rt}^F) and more responsive to shocks (an "indirect" effect). In Appendix B.4, I also linearize the aggregate population response (11):

$$\begin{aligned} \Delta l_{rt} \quad \approx \quad & \frac{1 - e^{-\gamma^I \mu^I}}{\gamma^I \mu^I} \mu_{rt}^F + \left(1 + \frac{\gamma^F \mu_{rt}^F}{\gamma^I \mu^I} \cdot \frac{1 - e^{-\gamma^I \mu^I}}{\gamma^I \mu^I} \right) \left(1 - \frac{1 - e^{-\gamma^I \mu^I}}{\gamma^I \mu^I} \right) (\Delta n_{rt} - \Delta z_{rt}^{sa}) \\ & + \left(1 + \frac{\gamma^F \mu_{rt}^F}{\gamma^I \mu^I} \cdot \frac{1 - e^{-\gamma^I \mu^I}}{\gamma^I \mu^I} \right) \left(1 - e^{-\gamma^I \mu^I} \right) (n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa}) \end{aligned} \tag{13}$$

Notice that the direct (i.e. independent) effect of μ_{rt}^F is smaller in (13) than (12), and the same is true of the indirect effect (on the response to shocks). This reflects the offsetting reduction in the internal response. In fact, as the internal elasticity γ^I becomes large, the effect of μ_{rt}^F on aggregate population dynamics goes to zero: i.e. there is perfect crowd-out. Intuitively, new immigrants do not "grease the wheels" if the wheels are already "greased", i.e. if the internal flows are already elastic.[8]

2.5 "Semi-structural" specification for crowding out

Estimation of (13), which accounts for local heterogeneity (along μ_{rt}^F) in population adjustment, is empirically demanding: I need to interact μ_{rt}^F with both current and lagged shocks. However, (7) and (8) imply a restriction which can reduce dimensionality: foreign intensity, μ_{rt}^F, enters the system exclusively through *realized* foreign inflows, λ_{rt}^F. A specification which imposes this restriction can be interpreted as "semi-structural"; whereas (12)-(13) are "reduced form" in that they collapse the impact of foreign inflows to the original μ_{rt}^F shock. I begin by writing a new expression for instantaneous population growth (in place of (9)), but now taking foreign inflows λ_r^F as given:

$$dl_r = \lambda_r^F + \gamma^I \mu^I \left(n_r - l_r - z_r^{sa}\right) \tag{14}$$

Crucially, the response to shocks no longer varies with r: holding the realized λ_{rt}^F fixed, changes in foreign intensity μ_{rt}^F have no effect on population adjustment. For small shocks, I show in Appendix B.3 that the discrete-time internal response $\lambda_{rt}^I \equiv \int_{t-1}^t \lambda_r^I(\tau)\, d\tau$ can then be approximated as:

$$\lambda_{rt}^I \approx \left(1 - \frac{1 - e^{-\gamma^I \mu^I}}{\gamma^I \mu^I}\right)\left(\Delta n_{rt} - \lambda_{rt}^F - \Delta z_{rt}^{sa}\right) + \left(1 - e^{-\gamma^I \mu^I}\right)\left(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa}\right) \tag{15}$$

For a given employment shock Δn_{rt} and initial conditions, (15) describes the extent to which foreign inflows λ_{rt}^F crowd out the internal contribution to adjustment. Crowd-out increases from 0 to -1 as the internal response becomes elastic ($\gamma^I \to \infty$). Notice the coefficients on Δn_{rt} and λ_{rt}^F are identical (up to their sign): this yields an overidentifying restriction which I exploit in the empirical analysis. Intuitively, these effects represent pure mobility responses to an equal change in local utility, as summarized by the local employment rate. Notice also that substituting (12) for λ_{rt}^F in the semi-structural specification (15) yields the "reduced form" specification described above.

Since I seek to identify crowd-out of the internal response to a *given* employment shock, the Δn_{rt} control is crucial. But this means the coefficient on λ_{rt}^F in (15) does not describe the *unconditional* effect of foreign inflows: local employment may be an important margin of adjustment. To derive the unconditional effect, it is necessary to reduce Δn_{rt} to its exogenous components. This is beyond the scope of this paper, but see Amior (2020) for such an analysis using the same dynamic framework.

[8] There is no corresponding crowd-out of the foreign response in this approximation, because I am linearizing around $\mu_{rt}^F = 0$.

Crowd-out in this model is driven entirely by the labor market. But natives' amenity valuations (which I have taken as given) may also play a role. Card, Dustmann and Preston (2012) show that hostility to immigration (at least in Europe) is largely motivated by concern over the composition of neighbors. On the other hand, natives may be able to escape migrant enclaves by moving within CZs (as in Saiz and Wachter, 2011; Fernandez-Huertas Moraga, Ferrer-i Carbonell and Saiz, 2017) rather than between them. In the context of (15), a disamenity effect can be represented by a negative correlation between the foreign inflow λ_{rt}^F and amenity change $\Delta a_{rt} = -\frac{1}{\epsilon^s}\Delta z_{rt}^{sa}$.

2.6 Foreign share of local population response

I now assess the foreign contribution to adjustment. It is useful to first define the time t "composite" employment shock, accounting for both current changes and initial deviations:

$$x_{rt} \equiv \left(1 - \frac{1-e^{-\gamma^I\mu^I}}{\gamma^I\mu^I}\right)\Delta n_{rt} + \left(1 - e^{-\gamma^I\mu^I}\right)(n_{rt-1} - l_{rt-1}) \tag{16}$$

In Appendix B.5, using (12) and (15), I show the mean foreign share of the population response to x_{rt} can be approximated (for small employment shocks) as:

$$\mathbb{E}\left[\frac{Cov\left(\lambda_{rt}^F, x_{rt}\right)}{Cov\left(\Delta l_{rt}, x_{rt}\right)}\right] \approx \left[\left(\frac{\gamma^F\bar{\mu}^F}{\gamma^I\mu^I} + \frac{Cov\left(\mu_{rt}^F, x_{rt}\right)}{Var\left(x_{rt}\right)}\right)^{-1} + \frac{1-e^{-\gamma^I\mu^I}}{\gamma^I\mu^I}\right]^{-1} \tag{17}$$

where $\bar{\mu}^F$ is the mean foreign intensity. For equal foreign and internal elasticities ($\gamma^F = \gamma^I$) and in the absence of spatial correlation, the foreign share of the population response (17) collapses to (approximately[9]) its share $\frac{\bar{\mu}^F}{\bar{\mu}^F+\mu^I}$ of migratory flows, which has averaged about 10% since the 1960s (see Figure 1). Any "excess" of the foreign response over 10% must be explained by either (i) relatively elastic foreign inflows (i.e. $\gamma^F > \gamma^I$) or (ii) spatial correlation between foreign intensity μ_{rt}^F and local shocks x_{rt}, i.e. $Cov\left(\mu_{rt}^F, x_{rt}\right) > 0$. In Section 4, I show the observed spatial correlation can account empirically for the excess foreign response (without recourse to large γ^F); and in Section 6, I show a dynamic model for μ_{rt}^F (disciplined by the data) can generate a correlation of sufficient size.

3 Data

3.1 Population

I identify foreign and (net) internal flows using decadal changes in local population stocks. To this end, I rely on decadal census data on individuals aged 16-64, for 722 Commuting

[9]This approximation works for small $\frac{\bar{\mu}^F}{\mu^I}$, since the $\frac{1-e^{-\gamma^I\mu^I}}{\gamma^I\mu^I}$ term is bounded between 0 and 1.

Zones (CZs) in the Continental US, over 1960-2010.[10]

The model disaggregates changes in log population Δl_{rt} into contributions from foreign and internal migration, i.e. λ_{rt}^F and λ_{rt}^I. Since I only observe population at discrete intervals, I cannot precisely identify λ_{rt}^F and λ_{rt}^I - though I can offer a close approximation. Let L_{rt}^F be the foreign-born population in area r at time t who arrived in the US in the previous ten years (i.e. since $t-1$). The total population change ΔL_{rt} can then be disaggregated into L_{rt}^F and a residual, $\Delta L_{rt} - L_{rt}^F$. And the log change can be written as:

$$\Delta l_{rt} \equiv \log\left(\frac{L_{rt}}{L_{rt-1}}\right) \equiv \log\left(\frac{L_{rt-1}+L_{rt}^F}{L_{rt-1}}\right) + \log\left(\frac{L_{rt}-L_{rt}^F}{L_{rt-1}}\right) - \log\left(1+\frac{L_{rt}^F}{L_{rt}}\cdot\frac{\Delta L_{rt}-L_{rt}^F}{L_{rt-1}}\right) \tag{18}$$

Motivated by (18), I approximate λ_{rt}^F with $\hat{\lambda}_{rt}^F$, and λ_{rt}^I with $\hat{\lambda}_{rt}^I$, where:

$$\hat{\lambda}_{rt}^F \equiv \log\left(\frac{L_{rt-1}+L_{rt}^F}{L_{rt-1}}\right) \tag{19}$$

$$\hat{\lambda}_{rt}^I \equiv \log\left(\frac{L_{rt}-L_{rt}^F}{L_{rt-1}}\right) \tag{20}$$

which leaves the final term of (18) as the approximation error. One might alternatively take first order approximations, i.e. $\lambda_{rt}^F \approx \frac{L_{rt}^F}{L_{rt-1}}$ and $\lambda_{rt}^I \approx \frac{\Delta L_{rt}-L_{rt}^F}{L_{rt-1}}$. These converge to λ_{rt}^F and λ_{rt}^I as they individually become small. However, convergence in the case of (19) and (20) merely requires that the product $\frac{L_{rt}^F}{L_{rt}} \cdot \frac{\Delta L_{rt}-L_{rt}^F}{L_{rt-1}}$ becomes small.

Of course, the residual contribution $\hat{\lambda}_{rt}^I$ does not just consist of internal flows. It accounts for the entire contribution of natives and "old" migrants (i.e. those who arrived in the US before $t-1$), part of which is "natural" growth and emigration from the US. Emigration is more relevant for the foreign-born (see e.g. Dustmann and Görlach, 2016), so it is useful to additionally study the component of $\hat{\lambda}_{rt}^I$ which is driven by natives alone:

$$\hat{\lambda}_{rt}^{I,N} \equiv \log\left(\frac{L_{rt-1}+\Delta L_{rt}^N}{L_{rt-1}}\right) \tag{21}$$

where L_{rt}^N is the local stock of natives at time t.

[10] CZs are county groups, developed by Tolbert and Sizer (1996) to approximate local labor markets, and popularized by Autor and Dorn (2013). Where possible, I use published census county-level aggregates from the National Historical Geographic Information System (Manson et al., 2017). Where necessary, like Amior and Manning (2018), I supplement this with data from microdata census extracts and (for the 2010 cross-section) American Community Survey samples of 2009-11, using the Integrated Public Use Microdata Series (Ruggles et al., 2017). See Appendix C.1 for further details. I begin the analysis in 1960: this is because I do not observe migrants' year of arrival in that year, so I cannot identify the foreign contribution to local population in the 1950s.

3.2 Comparability with Figure 1

A crucial insight of my paper is that the foreign contribution to local population adjustment vastly exceeds its share of gross migratory flows; and I reconcile this "excess" response using equation (17). Since I estimate adjustment using decadal CZ-level population changes, I would ideally compare these against ten-year migratory flows to CZs.

However, I do not observe these flows because of data limitations. Instead, I have motivated the paper (in Figure 1) using evidence from *annual* flows to *states*: this enables me to construct a consistent historical series. The mean foreign share of these flows over 1964-2010 in Panel B is 12%. Note this must exceed the foreign share of flows to CZs, because there is (mechanically) more mobility across CZs than states. But, it is not immediately obvious what difference the time horizon should make to the foreign share.

Though I cannot observe ten-year flows, I can construct five-year flows across CZs in some years. For example, in the 2000 census, respondents were asked where they lived five years previously. In my sample of working-age individuals, the foreign share (i.e. the fraction originating from abroad) of five-year flows is equal to 15.1%.[11] Reassuringly, this is similar to the foreign share of annual flows to states over 1996-2000 (in Figure 1), which is 15.5%. I conclude from this that annual state flows offer a reasonable benchmark.

3.3 Employment

In a contribution beyond Amior and Manning (2018), I adjust employment for local demographics. I have argued the employment rate is a sufficient statistic for local economic opportunity. But if different worker types value leisure differently, it will be conflated with local demographic composition. Though the model does not explicitly account for such heterogeneity, it may be represented by the local supply shifter z_r^s. This variation is not a problem if the Bartik instruments can exclude it. But the exclusion restriction may be violated if high-employment groups (such as the high-educated or foreign-born men: see Borjas, 2017) differ systematically in mobility.

I run probit regressions on each census microdata cross-section to purge local employment rates of detailed characteristics[12]: see Appendix C.2 for details. The composition-adjusted rate, $\tilde{ER}_r$, can be expressed as:

$$\log \tilde{ER}_r \equiv n_r - l_r - \tilde{z}_r^{sa} \tag{22}$$

[11] I compute the five-year inflow of foreign-born individuals from abroad (i.e. the numerator) using the 2000 census microdata. And I compute the gross five-year inflows to CZs (the denominator) using published statistics on migratory flows between US county pairs (which I aggregate to CZ-level). I take this data from the C2 A1 and B4 A1 tables on the Census 2000 Migration DVD, kindly made available by Kin Koerber: see *https://www.census.gov/population/www/cen2000/migration/mig_dvd.html*.

[12] Age, age squared, education (five categories), ethnicity (black, Asian, Hispanic), gender, foreign-born status, and where available, years in US and its square for immigrants, together with a rich set of interactions. See Appendix C.2.

where $\tilde{z}_r^{sa}$ is the component of the supply/amenity shifter z_r^{sa} attributable to observable local composition. I can then define $\tilde{n}_r$ as the composition-adjusted employment *level*:

$$\tilde{n}_r \equiv n_r - \tilde{z}_r^{sa} \equiv \log \tilde{ER}_r + l_r \tag{23}$$

and the instantaneous population response dl_r in (9) can be rewritten as:

$$dl_r = \mu_r^F + \gamma_r \left[\tilde{n}_r - l_r - (z_r^{sa} - \tilde{z}_r^{sa})\right] \tag{24}$$

where $(z_r^{sa} - \tilde{z}_r^{sa})$ is the residual component of supply (which is not attributed to local composition). In discrete time, by symmetry with (11), local population changes Δl_{rt} will then depend on (i) composition-adjusted employment growth, $\Delta \tilde{n}_{rt} \equiv \Delta \log \tilde{ER}_{rt} + \Delta l_{rt}$, and (ii) the lagged composition-adjusted rate $(\tilde{n}_{rt-1} - l_{rt-1}) \equiv \log \tilde{ER}_{rt-1}$. The identifying conditions are now weaker: the Bartik instruments need only exclude the *residual* supply/amenity effect $(z_r^{sa} - \tilde{z}_r^{sa})$.

3.4 Shift-share variables

I identify demand shocks using Bartik (1991) shift-shares, b_{rt}. This predicts local employment growth, conditional on initial industrial composition, by assuming each industry i grows at the same rate as elsewhere in the US:

$$b_{rt} = \sum_i \phi_{rt-1}^i \Delta n_{i(-r)t} \tag{25}$$

where ϕ_{rt-1}^i is the share of area r workers employed in 2-digit industry i (there are 57 categories) in $t-1$; and $\Delta n_{i(-r)t}$ is the national log employment change in industry i, excluding area r.[13] The instrument is intended to exclude unobserved supply and amenity effects in z_r^{sa}.

Similarly, I proxy foreign intensity μ_{rt}^F with an enclave shift-share, popularized by Altonji and Card (1991) and Card (2001). I motivate this shift-share theoretically in Appendix A.2. New migrants are known to cluster in established co-patriot communities, whether because of family ties, language or job networks. The shift-share predicts the local supply of new migrants by allocating them proportionately to community size. To express this predicted supply (which I denote $\hat{\mu}_{rt}^F$) in terms of its contribution to the *log* population change Δl_{rt}, I use an identical functional form to (19):

$$\hat{\mu}_{rt}^F = \log\left(\frac{L_{t-1} + \sum_o \phi_{rt-1}^o L_{o(-r)t}^F}{L_{rt-1}}\right) \tag{26}$$

[13]Goldsmith-Pinkham, Sorkin and Swift (2018) recommend this exclusion to address concerns about endogeneity to local supply shocks.

where ϕ^o_{rt-1} is the share of origin o migrants (I study 77 countries) residing in area r at time $t-1$, and $L^F_{o(-r)t}$ is the number of new origin o migrants (again excluding area r residents) who arrived in the US between $t-1$ and t.

Traditionally, the enclave shift-share $\hat{\mu}^F_{rt}$ is used to exclude local demand shocks z^d_{rt}. But I make no such claim: indeed, their correlation is crucial to generating the excess foreign response. I am able to relax this assumption by virtue of the sufficient statistic result: demand shocks z^d_r do not appear in the estimating equations (11), (12), (13) and (15), so I need only assume that $\hat{\mu}^F_{rt}$ excludes supply and amenity effects.

I construct the Bartik and enclave shift-shares using census microdata: see Appendix C.3 for further details. In Figure 2, I map the spatial distributions of composition-adjusted employment growth $\Delta\tilde{n}_{rt}$, foreign inflows $\hat{\lambda}^F_{rt}$, and both the Bartik and enclave shift-shares, averaged over all decades. All variables are typically larger in the North East, West, Texas and Florida. This speaks to the spatial correlation between employment conditions and migrant enclaves, which is crucial to my argument.

3.5 Amenity controls

Throughout, I control for the same observable amenity effects as Amior and Manning (2018): (i) presence of coastline[14] (ocean or Great Lakes); (ii) climate indicators[15], specifically maximum January and July temperatures and mean July relative humidity; (iii) log population density in 1900; and (iv) an index of CZ isolation (log distance to closest CZ, where distance is measured between population-weighted centroids). As their impact may vary with time, I interact each with a full set of year effects.

I do not control for time-varying amenities (such as crime), which may be endogenous to local conditions (Diamond, 2016). As such, the estimated population responses to employment shocks will account for both their direct (labor market) effect and any amenity-driven indirect effects.

4 Estimates of mean foreign contribution

4.1 Basic estimates

I begin by estimating the *mean* contribution of immigration to local population adjustment over the period, abstracting from heterogeneity in foreign intensity μ^F_{rt}. In line with

[14]The coastline data was borrowed from Rappaport and Sachs (2003).

[15]Rappaport (2007) shows that Americans have been moving to better weather.

(11), I estimate the following error correction model:

$$\Delta l_{rt} = \beta_{0t} + \beta_1 \Delta \tilde{n}_{rt} + \beta_2 \left(\tilde{n}_{rt-1} - l_{rt-1}\right) + A_r \beta_{At} + \varepsilon_{rt} \tag{27}$$

where t denotes decadal census year. I regress the log population change Δl_{rt} on the the (composition-adjusted) log employment change $\Delta \tilde{n}_{rt}$ and the lagged (composition-adjusted) employment rate $(\tilde{n}_{rt-1} - l_{rt-1})$, i.e. the initial conditions. The β_{0t} allow for year effects, and the vector A_r contains amenity controls (i.e. observable components of the z_r^{sa} terms in (11)), which themselves are interacted with year effects (in β_{At}). The error ε_{rt} contains any unobserved supply/amenity effects. I weight observations by lagged local population share and cluster standard errors by state.[16]

OLS estimates of (27) cannot be interpreted causally: unobserved supply shocks will bias β_1 estimates upwards, and β_2 will be biased down if these shocks are persistent (e.g. a positive supply shock will raise population growth but reduce the employment rate). To address this, I instrument $\Delta \tilde{n}_{rt}$ and $(\tilde{n}_{rt-1} - l_{rt-1})$ with current and lagged Bartiks, i.e. b_{rt} and b_{rt-1}. In theory, the lagged employment rate will depend on a distributed lag of Bartiks; but the first lag alone has sufficient power for the first stage. I set out the first stage estimates in columns 1-2 of Table 1. The current Bartik picks up the bulk of the effect on $\Delta \tilde{n}_{rt}$, and the lagged Bartik the effect on $(\tilde{n}_{rt-1} - l_{rt-1})$, with large Sanderson-Windmeijer (2016) F-statistics (which account for multiple endogenous variables).

I set out estimates of β_1 and β_2 in Panel A of Table 2. The OLS effects are 0.86 and 0.25 respectively (column 1), and the IV effects 0.75 and 0.55 (with small standard errors: column 2); so the OLS bias is in the expected direction. These numbers indicate large but incomplete population adjustment over one decade to contemporaneous shocks and initial conditions. Interestingly, they are somewhat larger than estimates based on raw (i.e. non-adjusted) employment variables: see Appendix Table A5.[17] Note that the null hypothesis of no dynamic effects (i.e. that the initial employment rate has no effect) is consistently rejected with considerable power, despite the long decadal time horizons.

Column 3 replaces the dependent variable with the approximate foreign contribution $\hat{\lambda}_{rt}^F$ (as defined by (19)), and column 4 with the residual contribution $\hat{\lambda}_{rt}^I$. The approximation appears reasonable: β_1 in columns 3 and 4 sum to 0.76, and β_2 to 0.58 - very close to the column 2 estimates. Remarkably, new migrants account for 32%

[16] CZs are allocated to the state which accounts for the largest population share.

[17] Using raw employment, I estimate β_1 as 0.63 and β_2 as 0.39. The difference is intuitive. The college educated population is known to respond more strongly (see below), but these individuals also have higher employment rates. As a result, the change in raw employment, Δn_{rt}, will exceed the composition-adjusted change, $\Delta \tilde{n}_{rt}$; so the population response to the latter will be larger.

of the overall population response to contemporaneous shocks (β_1) and 57% of the response to the lagged employment rate (β_2).[18] What is the foreign contribution over the long run? To answer this, consider a one-off employment shock. Foreign inflows contribute 32% of the initial 0.748 population response; and they contribute 57% of the remaining $(1 - 0.748) = 0.252$ response. Taking a weighted average of the two gives: $(0.748 \times 32\%) + (0.252 \times 57\%) = 38\%$.

I also report the contribution of natives alone, i.e. $\hat{\lambda}_{rt}^{I,N}$ from (21). The numbers are similar to column 4: this indicates that old migrants (those already in the US in $t-1$) contribute little to the population response, unlike in Cadena and Kovak (2016) where they are dominant. Note this implies that selective emigration (of old migrants) does not play an important role in local adjustment. One concern is that the estimated contribution of old migrants may be conflated with generational shifts (from foreign-born residents to their native children), but I show in Appendix F.4 that accounting for this makes little difference. I also show in Appendix Table A9 that the foreign contribution is not dominated by any particular origin group - again, unlike in Cadena and Kovak.

4.2 What explains the foreign contribution?

The foreign contribution greatly exceeds the foreign share of gross flows, $\frac{\bar{\mu}^F}{\bar{\mu}^F + \mu^I}$, which has averaged about 10% since the 1960s: see Section 3.2. Based on (17), there are two possible explanations: a larger foreign sensitivity ($\gamma^F > \gamma^I$) or spatial correlation between foreign intensity μ_{rt}^F and employment shocks.

In Panel B, I attempt to disentangle these empirically by controlling for the enclave shift-share $\hat{\mu}_{rt}^F$ (which proxies the foreign intensity). Of course, to the extent that $\hat{\mu}_{rt}^F$ measures the foreign intensity μ_{rt}^F with error, this will understate the true effect. Still, this wipes away much of the foreign response to local shocks (column 3). Relative to the overall population response (in column 2), the foreign share declines to 7% of the β_1 effect and 28% of β_2. Over the long run, these numbers imply a $(0.735 \times 7\%) + ((1 - 0.735) \times 28\%) = 13\%$ foreign contribution. This is remarkably close to the 10% share of gross flows. That is, statistically at least, the excess foreign response is almost entirely explained by spatial correlation between shocks and enclaves - without any recourse to a larger foreign sensitivity. In Section 6 below, I attribute this spatial correlation to a local snowballing effect, driven by the dynamics of enclaves and persistent local shocks. A dynamic model (disciplined by the data) shows this persistence is quantitatively sufficient to account for the effect.

Interestingly, the *overall* population response is unaffected by the $\hat{\mu}_{rt}^F$ control (column

[18]The mean foreign contributions to β_1 and β_2 are smaller once I omit population weights (Appendix Table A7), since new migrants cluster in larger CZs. They are also smaller in OLS (Appendix Table A1): 5 and 36% respectively. In the same table, I offer (genuine) reduced form estimates (regressing population changes directly on the Bartik shift-shares): these offer a similar picture to the IV estimates.

2): the now smaller foreign contribution to adjustment is offset by a larger residual contribution (column 4). This speaks to the "indirect" crowding out effect of foreign intensity μ_{rt}^F (see Section 2.4), and I estimate this more explicitly below. Notice also there is clear "direct" crowd-out: $\hat{\mu}_{rt}^F$ raises the foreign contribution one-for-one (column 3), offset by a similar decline in the residual (column 4).

4.3 Native and migrant employment rate responses

For convenience, the model treats natives and migrants as perfect substitutes. But local employment shocks (and the associated population responses) may affect natives and migrants differently. To study this, in columns 6-8 of Table 2, I replace the dependent variable of (27) with log employment rate changes: first, the aggregate rate $\Delta\left(\tilde{n}_{rt} - l_{rt}\right)$, and then the native and migrant-specific rates. The latter two are adjusted using the same procedure outlined in Section 3.3, but with the sample restricted to natives or migrants.[19] The column 6 estimates are merely transformations of those in column 2: the effect of employment growth is equal to $1 - \beta_1$ in (27), while that of the lagged employment rate is $-\beta_2$. In words, a larger population response implies a smaller employment rate effect. But, notice the responses of the native and migrant employment rates (columns 7-8) are similar - both to employment shocks and the enclave shift-share $\hat{\mu}_{rt}^F$.

4.4 Foreign contribution by education

I now show that the foreign contribution is substantial among both high and low education groups. The model above does not account for such heterogeneity. But as Amior and Manning (2018) note, the sufficient statistic result can be applied more generally. One can write labor supply functions like (2) and utility functions like (4) for individual education groups. And combining the two, the education-specific employment rate can serve as a sufficient statistic for each group's employment opportunities. The ECM equation (11) can then legitimately be estimated separately for distinct education groups - irrespective of the productive relationship between these groups.

With this in mind, I replace all variables of interest in (27) with college graduate and non-graduate equivalents. Again following the procedure of Section 3.3, I adjust employment for demographic composition, but this time using education-specific samples; and I also construct new Bartik and enclave shift-shares using these samples.

[19] 11 small CZs in the 1960s are omitted from column 8: they do not offer a sufficient migrant sample to deliver fixed effect estimates in the probit regressions, so I cannot compute migrant-specific composition-adjusted employment rates.

Table 3 presents the IV estimates. Comparing columns 1 and 5, the aggregate population response is significantly larger for college graduates (as in Amior and Manning, 2018): the graduate response to current employment growth, β_1, is now 1-for-1. The standard error on the graduate β_2 is very large, but this is not surprising: the large β_1 implies little deviation in local employment rates. I leave the first stage estimates to Appendix Table A3: as before, each instrument picks up the bulk of the variation for the corresponding endogenous variable. The F-statistics are very large for non-graduates (in excess of 50), but below 10 for graduates: this reflects the difficulty of identifying the lagged employment rate effect.

The foreign contribution is large for both groups - and especially for graduates. Foreign migration accounts for 60% of the graduate β_1 response (compare columns 1 and 2), and 33% for non-graduates (columns 5-6). Indeed, the larger foreign contribution for graduates accounts for the entire difference in aggregate responses across education groups: the residual responses are similar. Finally, similarly to Table 2, the enclave control $\hat{\mu}_{rt}^F$ eliminates the bulk of the foreign response for both education groups.

5 Estimates of crowding out

5.1 Local heterogeneity in population responses

The estimates above reveal a substantial foreign contribution to local population adjustment. What are the implications for adjustment overall? As the model shows, this will depend on the extent to which the foreign contribution crowds out internal mobility. To address this question, I study how population responses vary (over space and time) with the enclave shift-share $\hat{\mu}_{rt}^F$. I base my specification on (13):

$$\begin{aligned} \Delta l_{rt} \quad &= \quad \beta_{0t}^h + \beta_1^h \Delta \tilde{n}_{rt} + \beta_2^h \left(\tilde{n}_{rt-1} - l_{rt-1} \right) + A_r \beta_{At}^h \\ &\quad + \left[\beta_{0\mu}^h + \beta_{1\mu}^h \Delta \tilde{n}_{rt} + \beta_{2\mu}^h \left(\tilde{n}_{rt-1} - l_{rt-1} \right) + A_r \beta_{A\mu}^h \right] \hat{\mu}_{rt}^F + \varepsilon_{rt} \end{aligned} \tag{28}$$

where $\hat{\mu}_{rt}^F$ is now interacted with employment growth $\Delta \tilde{n}_{rt}$, the lagged employment rate $(\tilde{n}_{rt-1} - l_{rt-1})$ and the amenity effects A_r, in line with (13). This allows for heterogeneous foreign responses to both employment and amenity differentials. I have recentered all variables interacted with $\hat{\mu}_{rt}^F$ to zero, so $\beta_{0\mu}^h$ describes the impact of $\hat{\mu}_{rt}^F$ for the average CZ. This specification is similar in spirit to Cadena and Kovak (2016); but they do not account for local dynamics, and they study heterogeneity along the support of the initial Mexican population share (rather than the enclave shift-share). My focus on the shift-share is motivated by my model: I am interested in how population adjustment differs in places with better access to *new* immigrants (given their remarkable contribution to local adjustment in Table 2); and this is precisely what the shift-share predicts.

I have introduced two new endogenous variables, so I need two additional instruments: I use interactions between $\hat{\mu}_{rt}^F$ and the current and lagged Bartiks. Table 4 reports the first stage estimates: each instrument has a large positive effect (with small standard error) on its corresponding endogenous variable. Identification requires only that the instruments are independent of unobserved supply/amenity effects. This is because the employment change and lagged employment rate fully summarize labor market opportunities, so the error ε_{rt} should in principle contain no demand effects: see equation (13).

Table 5 reports estimates of (28). I begin with OLS in column 1. The interactions are insignificant for the contemporaneous shock and positive for the lagged employment rate - though endogeneity is clearly a problem. When I apply IV in column 2, the interactions are statistically insignificant for both the current shock and initial conditions, and the direct effect of $\hat{\mu}_{rt}^F$ is also insignificant. That is, the aggregate population response is not significantly different in areas with a larger foreign supply of migrants.

I now disaggregate the aggregate population response into its components. In column 3, I replace the dependent variable with the foreign contribution $\hat{\lambda}_{rt}^F$. Consistent with (12) in the model, the interactions pick up the entire effect. In CZs with $\hat{\mu}_{rt}^F = 0$, employment shocks draw no foreign inflows. But at $\hat{\mu}_{rt}^F = 0.1$, which is the 98th percentile of $\hat{\mu}_{rt}^F$ (the maximum is 0.29: the distribution is heavily skewed), the foreign responses to $\Delta\tilde{n}_{rt}$ and $(\tilde{n}_{rt-1} - l_{rt-1})$ are a remarkable 0.49 and 0.74 respectively.

As the model predicts, these larger foreign contributions are offset by significantly lower internal mobility. Moving from $\hat{\mu}_{rt}^F = 0$ to 0.1, the residual contribution (column 4) declines from 0.81 to 0.28 for the $\Delta\tilde{n}_{rt}$ response, and from 0.60 to -0.06 for $(\tilde{n}_{rt-1} - l_{rt-1})$. It also fully offsets the direct effect of $\hat{\mu}_{rt}^F$ (i.e. without the interactions) on local population. Though I cannot reject perfect crowd-out, the estimates do admit the possibility of incomplete crowd-out: the standard errors on the offsetting residual response (column 4) are close to 40% of the $\beta_{2\mu}^h$ coefficient, though they are much smaller for $\beta_{0\mu}^h$ and $\beta_{1\mu}^h$.

Column 5 reports the contribution of natives alone. The interaction effects exceed those of column 4, implying that old migrants amplify the foreign contribution in high-$\hat{\mu}_{rt}^F$ areas (despite contributing little *on average* in Table 2), while natives account for (more than) the entire crowding out effect. This can be interpreted as a mechanical composition effect: old migrants disproportionately reside in high-$\hat{\mu}_{rt}^F$ CZs, so they should contribute a larger share (and natives a smaller share) of population adjustment in these places.

In the final three columns, I replace the dependent variable with changes in log employment rates. As in Table 2, the coefficients in column 6 are merely transformations of those in column 2. Given the insignificant interaction effects, these results fail to confirm Borjas' (2001) hypothesis that new immigrants eliminate local labor market disparities (which I summarize here by local employment rates); and the same applies to the native and migrant employment rates individually.[20]

In Appendix Table A2, I offer OLS and reduced form estimates corresponding to Table 5: these also point to large crowd-out. In Appendix F (and the corresponding Tables A5-A7), I study the sensitivity of the IV estimates in Tables 2 and 5. The crowding out effects are robust to including CZ fixed effects, which pick up (supply-driven) local population trends: this is a demanding test in such a short panel. They are also robust to omitting the lagged employment rate and to using raw (instead of composition-adjusted) employment variables. Since adjusting local employment for observable demographics makes little difference to the result, one may be less concerned about the influence of unobservables. Omitting the amenity-$\hat{\mu}_{rt}^F$ interacted controls makes little difference to the coefficients, but the standard errors do become larger. One may be concerned that the crowding out effects are driven by outliers with very large $\hat{\mu}_{rt}^F$ (given the skew in this variable), but dropping observations with $\hat{\mu}_{rt}^F > 0.1$ makes little difference. The crowding out result is also robust to removing the population weights, at least after restricting the sample to CZs with population exceeding 50,000.

5.2 Implications for trends in regional mobility

This crowd-out may help account for the contemporaneous decline in regional mobility. Since the 1960s, the rate of cross-state migration has approximately halved (Figure 1). Numerous explanations have been proposed, including declining location-specific occupational returns (Kaplan and Schulhofer-Wohl, 2017), greater barriers to mobility (Dao, Furceri and Loungani, 2017) and a declining rate of job transitions (Molloy, Smith and Wozniak, 2017). But it may also reflect accelerating immigration: to the extent that new immigrants respond to local employment disparities, this obviates the need for existing US residents to move (at potentially great cost) themselves. Molloy, Smith and Wozniak themselves raise this possibility, but they are dubious for two reasons. First, they find that internal flows to low (as well as high) immigration states fell noticeably; but this may reflect (omitted) weak demand conditions. And second, at the national level, they find internal mobility declined among high and low educated natives alike. This undermined their confidence in the hypothesis, because they expected immigration to be more salient among the low educated - but the results in Table 3 suggest otherwise.

To quantify the impact on internal mobility, note that the mean enclave shift-share $\hat{\mu}_{rt}^F$ (which predicts foreign inflows) has grown from 0.010 in the 1960s to 0.056 in the 2000s. As a result of this change, the estimates of Table 5 (column 4) predict that the mean internal response to contemporaneous employment shocks $\Delta\tilde{n}_{rt}$ will have fallen from 0.76

[20] Cadena and Kovak (2016) argue that Mexican-born US residents help smooth local employment rates. But I find no evidence in Table 2 that longer-term migrants contribute substantially to local labor market adjustment. See also the reconciliation in Appendix H.

to 0.51 (a 33% decline), and the mean response to initial deviations ($\tilde{n}_{rt-1} - l_{rt-1}$) from 0.53 to 0.23 (a 57% decline). Aggregating these numbers, the long-run internal response to a one-off employment shock will then have fallen by 39%.[21] Of course, other factors may well be contributing to the decline in regional mobility. But these numbers suggest that immigration likely played an important role.

5.3 "Semi-structural" estimates

The analysis above offers a "reduced form" perspective on the impact of the enclave shift-share, $\hat{\mu}^F_{rt}$. Conditional on employment, the results suggest $\hat{\mu}^F_{rt}$ has no significant effect on local population: foreign inflows crowd out the contribution of internal mobility, both directly and in response to employment shocks. But accounting simultaneously for dynamics and local heterogeneity is empirically demanding, and this makes the standard errors larger. I now estimate the more tractable "semi-structural" specification, which imposes that the entire effect of $\hat{\mu}^F_{rt}$ in Table 5 comes through *realized* foreign inflows. The question then becomes: for a *given* employment shock $\Delta\tilde{n}_{rt}$ and initial conditions, how do foreign inflows (in response to the shock or otherwise) affect internal mobility? In line with equation (15), I estimate the following specification:

$$\hat{\lambda}^I_{rt} = \delta_{0t} + \delta_1 \hat{\lambda}^F_{rt} + \delta_2 \Delta\tilde{n}_{rt} + \delta_3 \left(\tilde{n}_{rt-1} - l_{rt-1}\right) + A_r \delta_{At} + \varepsilon_{rt} \tag{29}$$

where $\hat{\lambda}^I_{rt}$ and $\hat{\lambda}^F_{rt}$ are the approximate residual and foreign contributions. As I have stressed above, δ_1 is a "conditional" crowding out effect: employment may be an important margin of adjustment to foreign inflows, but its contribution is partialled out in (29). Given my focus is the migratory adjustment to a *given* employment shock, this "conditional" effect is the relevant one for my research question.

Conditional on the employment controls (and given the sufficient statistic result), equation (15) shows that the ε_{rt} error in (29) should only contain unobserved supply/amenity effects. In an effort to exclude these, I instrument the three endogenous variables ($\hat{\lambda}^F_{rt}$, $\Delta\tilde{n}_{rt}$ and $\tilde{n}_{rt-1} - l_{rt-1}$) with the enclave shift-share $\hat{\mu}_{rt}$ and the current and lagged Bartiks, b_{rt} and b_{rt-1}. Table 6 reports first stage estimates, corresponding to the specifications of Table 7: these have substantial power.

I present estimates of (29) in Table 7. These reveal substantial crowd-out, consistent with the results above. The OLS estimate of δ_1 in column 1 is -0.88: i.e. conditional on local employment, a foreign inflow raising local population by 1 log point is associated

[21] Following a one-off employment shock, a fraction 0.748 of the overall population response occurs contemporaneously (see column 2 of Table 2), and the remaining 0.252 comes in response to initial deviations. Therefore, the long-run response will have declined by $(0.748 \times 33\%) + (0.252 \times 57\%) = 39\%$.

with a net outflow (of natives and earlier migrants) of 0.88. But this may be conflated with omitted supply shocks, which influence both foreign inflows and employment.

Column 2 applies the instruments. δ_1 is a little larger than OLS (0.91), with a standard error of just 0.07. The estimate is not driven by outliers, as I show in scatter plots of partialled variables in Appendix Figure A2. The small gap between the OLS and IV estimates is perhaps not surprising: conditional on the employment controls, equation (15) suggests that any bias can only be due to omitted supply (and not demand) shocks.

The response to employment shocks is also worthy of comment. Conditional on $\hat{\lambda}^F_{rt}$, the coefficients on the employment variables effectively describe the internal response in the absence of foreign inflows. Notice the coefficients in column 2 (0.74 and 0.56) are almost identical to the aggregate population responses in column 3 of Table 2 (0.75 and 0.55). This is consistent with perfect crowd-out of the internal response.

In columns 3-4, I re-estimate the semi-structural equation but replacing the key variables (foreign and residual contributions and employment shocks) and their instruments with education-specific equivalents. Crowd-out is larger for non-graduates, with a δ_1 of -0.98, compared to -0.68 for graduates. I leave the first stages to Appendix Table A4: the F-statistics all exceed 70 for non-graduates, but are below 10 for graduates. As before, this reflects the difficulty of identifying the latter's lagged employment rate effect.

In Appendix Table A10, I study the sensitivity of my basic IV estimate of δ_1 (in column 2) to controls, sample and weighting. Without any employment or amenity controls, δ_1 varies substantially over time. This reflects the concerns of Borjas, Freeman and Katz (1997) on the instability of spatial correlations, and it offers strong motivation for pooling many decades. But reassuringly, δ_1 becomes much more stable (and larger) when I control for employment effects: the average δ_1 increases from -0.53 to -0.75. And with the amenity controls, it increases to -0.91. Once all controls are included, the estimates are also robust to dropping the population weights. This suggests crowd-out is not markedly different in larger CZs. The stability of these estimates is remarkable, and it offers strong ex post support for the empirical specification.

5.4 Challenges to identification

The enclave instrument's validity depends on the exogeneity of the initial (origin-specific) migrant population shares (Goldsmith-Pinkham, Sorkin and Swift, 2018). But Table 2 shows these shares are correlated with local demand shocks, confirming the fears of Borjas (1999). This is a consequence of local dynamics: the initial migrant shares are themselves an outcome of *historical* demand shocks, which predict *current* internal mobility - both because of sluggish adjustment and also serial correlation in the shocks themselves. (Indeed, it is this very correlation which generates the excess foreign response to local shocks.) Persistence in the enclave instrument also makes it difficult to disentangle the impact of current and historical foreign inflows, as Jaeger, Ruist and Stuhler (2018) have emphasized in important work. To address the latter challenge, Jaeger, Ruist and Stuhler propose controlling for historical foreign inflows or its lagged enclave instrument - but this leaves the problem of omitted demand shocks unsolved.

I instead impose more structure. In principle, the lagged employment rate is a sufficient statistic for the impact of all historical demand and migration shocks (i.e. up to the period when the enclaves are measured), whether these shocks are observed or not. This offers a theoretical rationale for Pischke and Velling's (1997) proposal to control for the lagged unemployment rate. Since the current employment growth control $\Delta \tilde{n}_{rt}$ does the same for contemporaneous demand shocks, I need only assume that the enclave instrument $\hat{\mu}^F_{rt}$ excludes unobserved supply and amenity effects: see equation (15). Even without the $\Delta \tilde{n}_{rt}$ control though (i.e. in an "unconditional" specification: see Amior, 2020), new innovations to demand should not pose a major threat: as I have argued, the endogeneity of historical enclaves is a consequence of the foreign response to *historical* shocks, and the lagged employment rate already partials out this history. See Section 6 for a more formal exposition of these dynamics.

To test whether this "sufficient statistic" is performing its function effectively, I now control for the lagged enclave shift-share $\hat{\mu}^F_{rt-1}$. As column 8 of Table 6 shows, $\hat{\mu}^F_{rt-1}$ does adversely affect the initial employment rate in the *first* stage - as one might expect. But reassuringly, conditional on the initial employment rate (which is intended to summarize all historical shocks), $\hat{\mu}^F_{rt-1}$ has no effect on internal flows in the *second* stage: see column 5 of Table 7. In contrast, when I drop the lagged employment rate in column 6 (and replace it with its lagged Bartik instrument), $\hat{\mu}^F_{rt-1}$ picks up much of the negative effect. Thus, though internal flows do respond sluggishly to immigration, the lagged employment rate accounts fully for these dynamics.

Notice also that column 6 identifies less crowd-out: δ_1 falls from -0.90 to -0.71. This likely reflects a positive correlation between the enclave instrument and omitted historical *demand* shocks, which are partialled out in column 5 by the lagged employment rate.

Finally, Peri (2016) emphasizes the importance of checking for pre-trends. In column 7, I replace the dependent variable (the internal contribution, $\hat{\lambda}^I_{rt}$) with its lag, $\hat{\lambda}^I_{rt-1}$. Remarkably, this is entirely picked up by the *lagged* enclave shift-share $\hat{\mu}^F_{rt-1}$ and Bartik b_{rt-1}. In contrast, the *current* foreign contribution $\hat{\lambda}^F_{rt}$ and Bartik b_{rt} are statistically insignificant. This suggests I can empirically disentangle current from historical shocks. Certainly, this endeavor is aided by pooling multiple decades of data.

5.5 Why is the crowding out effect so large?

Based on the model, the crowding out effect is too large to be driven by the labor market alone. According to (15), λ^I_{rt} should respond equally to foreign inflows and employment shocks: i.e. $\delta_1 = -\delta_2$ in the empirical specification (29). The intuition is that both elasticities represent (in principle) pure mobility responses to changes in local employment opportunities - as summarized by the local employment rate (the sufficient statistic). At the bottom of each column, I test this hypothesis more formally. It cannot be rejected for OLS in column 1, but it is rejected for IV in column 2 - with a p-value of 0.013. In that specification, δ_1 is estimated as -0.91 and δ_2 as 0.74. The gap is entirely driven by the low educated: compare columns 3 and 4. Note that any imperfect substitutability between natives and migrants should *moderate* the δ_1 effect (relative to the model's predictions), so it would make the result even harder to explain.

What accounts for these differences? I offer three explanations. First, at least in the semi-structural specification, my δ_1 estimate may be conflated with (return) emigration of earlier migrants.[22] CZs with larger enclaves can mechanically expect more such emigration. Indeed, though earlier migrants contribute little to the response to employment shocks, they account for 40% of the crowding out effect (compare columns 2 and 8 of Table 7). To address this point, I replace the foreign contribution $\hat{\lambda}^F_{rt}$ on the right-hand side with the total migrant contribution[23] (though this will neglect any internal response from earlier migrants). Column 9 reports a crowding out effect of -0.82, which is now insignificantly different from the employment response.

A second factor is undercoverage of undocumented migrants: if foreign inflows are systematically underreported, this may may bias upward their estimated impact. However, Amior (2020) shows that the employment control $\Delta\tilde{n}_{rt}$ eliminates most of this bias: it can only account for about 30% of the gap between δ_1 and δ_2.

Third, native distaste for migrant enclaves may play a role: see Section 2.5. Given this effect falls outside the labor market, it can cause δ_1 to exceed δ_2. And it can also account for the larger crowd-out among non-graduates (columns 3-4): Card, Dustmann and Preston (2012) and Langella and Manning (2016) find that lower educated natives care more about compositional amenities. And Saiz and Wachter (2011) show that lower educated migrants trigger more "native flight" across local neighborhoods.

6 Dynamic response to employment shocks

Using my estimates, I now simulate the impulse response to local employment shocks - to assess whether the model's dynamics can quantitatively account for the "excess" foreign population response. Table 2 shows the excess response is almost entirely explained (at least statistically) by spatial correlation between local employment conditions and

[22] Comparing cohort sizes across census observations, Ahmed and Robinson (1994) estimate that about 10% of foreign-born residents emigrate in the subsequent decade.

[23] Analogously to (21), I define this as $\log\left(\frac{L_{rt-1}+\Delta L^M_{rt}}{L_{rt-1}}\right)$, where L^M_{rt} is the local stock of *all* foreign-born individuals (both new immigrants and longer-term residents).

migrant enclaves. My claim is that this correlation is driven by the dynamics of migrant enclaves, in the face of persistent local shocks. I begin this section by estimating an evolutionary process for the enclave shift-share $\hat{\mu}^F_{rt}$, and I then study the quantitative implications for the foreign response to local shocks.

I have chosen to take employment as given in this exercise. One might alternatively simulate the response to a demand shock (i.e. z^d_r in (3)), allowing employment to adjust endogenously to local population. However, accounting for this feedback would distract from my main goal: to understand the foreign *share* of the population response. In any case, Blanchard and Katz (1992) and Amior and Manning (2018) find that employment contributes little to local adjustment: population bears almost the entire burden.

Of course, there may be other ways to explain the spatial correlation between enclaves and employment rates. In particular, strong employment conditions may themselves be a *consequence* of foreign inflows.[24] This would require an elasticity of local employment to foreign inflows which exceeds one - implying that immigration amplifies local employment shocks, rather than "greasing the wheels". However, Table 2 rejects this hypothesis: the enclave shift-share $\hat{\mu}^F_{rt}$ (which predicts foreign inflows) has a small negative effect on employment rates (columns 6-8). This negative effect is also consistent with Card (2001), Smith (2012), Edo and Rapoport (2017), Gould (2019) and Amior (2020).

6.1 Local evolution of enclave shift-share

In the model in Section 2, I take the foreign intensity μ^F_{rt} as given. But I now build a simple empirical model for its evolution. I begin, in the first column of Table 8, by regressing the enclave shift-share $\hat{\mu}^F_{rt}$ (which proxies for foreign intensity) on its lag. This yields a precisely estimated 1: $\hat{\mu}^F_{rt}$ has a unit root. Consequently, local enclaves will be permanently shaped by historical shocks. As Jaeger, Ruist and Stuhler (2018) note, the persistence in $\hat{\mu}^F_{rt}$ reflects stickiness in migrant settlement patterns (the ϕ^o_{rt-1} in equation (26)) and persistence in aggregate-level foreign inflows by country of origin (the $L^F_{o(-r)t}$).

Since $\hat{\mu}^F_{rt}$ is based on $t-1$ enclaves, changes between $\hat{\mu}^F_{rt-1}$ and $\hat{\mu}^F_{rt}$ will reflect local demographic changes between $t-2$ and $t-1$. This will of course depend on foreign inflows $\hat{\lambda}^F_{rt-1}$ between $t-2$ and $t-1$. Including $\hat{\lambda}^F_{rt-1}$ deprives me of one decade of data, but this does not affect the unit root (column 2). As expected, $\hat{\lambda}^F_{rt-1}$ enters positively in column 3. The effect is less than one (about 0.5), which reflects diffusion of earlier migrants. Notice also the coefficient on $\hat{\mu}^F_{rt-1}$ falls to about 0.5: this is because $\hat{\mu}^F_{rt-1}$ enters $\hat{\lambda}^F_{rt-1}$ with a coefficient of about 1 (see column 3 of Table 2). Column 4 controls

[24]For example, Peri (2012) finds that immigration boosts local TFP growth.

additionally for the lagged internal contribution, $\hat{\lambda}^I_{rt-1}$. This has no effect, which suggests internal flows typically have a balanced composition of native and foreign-born workers.

6.2 Impulse response

To see how this amplifies the foreign response, I study the following four-equation system:

$$\lambda^F_{rt} = \mu^F_{rt}\left[1 + \beta^F_{1\mu}\Delta\tilde{n}_{rt} + \beta^F_{2\mu}\left(\tilde{n}_{t-1} - l_{t-1}\right)\right] \tag{30}$$

$$\lambda^I_{rt} = \delta_1\lambda^F_{rt} + \delta_2\Delta\tilde{n}_{rt} + \delta_3\left(\tilde{n}_{rt-1} - l_{rt-1}\right) \tag{31}$$

$$l_{rt} = l_{rt-1} + \lambda^F_{rt} + \lambda^I_{rt} \tag{32}$$

$$\Delta\mu^F_{rt} = \theta\left(\lambda^F_{rt-1} - \mu^F_{rt-1}\right) \tag{33}$$

Equation (30) describes the foreign response to local employment shocks: based on the IV estimates of Table 5 (column 3), $\beta^F_1 = 4.908$ and $\beta^F_{2\mu} = 7.407$. (31) is the semi-structural equation for the internal response: based on column 2 of Table 7, $\delta_1 = -0.913$, $\delta_2 = 0.743$ and $\delta_3 = 0.556$. (32) updates local population l_{rt}, based on the foreign and internal contributions. And (33) describes the evolution of μ^F_{rt}: based on column 3 of Table 8, I impose a unit root and calibrate θ to 0.469.

Persistence in the local employment shocks is crucial to understanding the excess foreign response. I illustrate this in Figure 3, which traces out the impulse responses to exogenous $\Delta\tilde{n}_{rt}$ shocks - both temporary and permanent. At time 0, I normalize log employment and population to zero, and I set foreign intensity μ^F_{rt} to the sample mean, 0.033. In Panel A, I study a temporary 0.1 shock to $\Delta\tilde{n}_{rt}$ at time (decade) 1: that is, $\Delta\tilde{n}_{rt} = 0.1$ at $t = 1$, and zero thereafter. The log employment rate initially grows by just 0.02, mainly because of a large internal response. The foreign response is initially small; but unlike the internal response, it persists - despite the swift elimination of the employment shock. In this sense, the foreign inflow "overshoots". In response, the internal flows eventually turns negative - though not sufficiently to prevent a slight dip in the employment rate.[25]

However, if the shock persists, there is no such "overshooting": foreign inflows are strongly directed to high-employment areas, where they are most needed. This is clear from Panel B, which simulates a permanent 0.1 shock to local employment growth: i.e. $\Delta\tilde{n}_{rt} = 0.1$ for all $t > 0$. It is a well known feature of ECMs that permanent shocks cause permanent deviations in outcomes: the employment rate eventually stabilizes at about 0.03.[26] This permanent deviation elicits an explosive foreign inflow, driven by feedback

[25]This dip occurs because crowd-out is not quite one-for-one: i.e. $\delta_1 < 1$.

[26]The employment rate does begin to contract (very slowly) by the fourth decade, due to the overshooting foreign response and incomplete crowd-out.

between λ^F_{rt} and burgeoning local enclaves μ^F_{rt}, which helps to satisfy the ever-expanding demand. By decade 4, the internal contribution is almost fully crowded out - and the foreign contribution accounts for almost the entire population response. Thus, the more persistent are local shocks, the greater the foreign response.

6.3 Accounting for the excess foreign contribution

Panel B shows that persistent shocks amplify the foreign response, due to the enclave dynamics. Can the model quantitatively account for the "excess" contribution observed in Table 2? Equation (17) above sets out an expression for the mean foreign share of the population response to x_{rt}, a "composite" employment shock (defined in (16)) which accounts for both the contemporaneous shock and lagged employment rate. This expression depends on the linear projection of foreign intensity μ^F_{rt} on x_{rt}. Using the four-equation system above, I show in Appendix B.6 that this projection can theoretically be approximated by:

$$\frac{Cov\left(\mu^F_{rt}, x_{rt}\right)}{Var\left(x_{rt}\right)} \approx \theta \frac{\gamma^F \bar{\mu}^F}{\gamma^I \mu^I} \sum_{i>0} \frac{Cov\left(x_{rt}, x_{rt-i}\right)}{Var\left(x_{rt}\right)} \tag{34}$$

This is increasing in (i) the elasticity θ of migrant enclaves to foreign inflows and (ii) the persistence of local shocks, where $\sum_{i>0} \frac{Cov(\tilde{x}_{rt}, \tilde{x}_{rt-i})}{Var(\tilde{x}_{rt})}$ is the infinite sum of x_{rt} autocorrelations. Plugging (34) into (17), and imposing full crowd-out (i.e. $\frac{1-e^{-\gamma^I \mu^I}}{\gamma^I \mu^I} = 0$), the mean foreign share of the response to x_{rt} can then be approximated as:

$$\mathbb{E}\left[\frac{Cov\left(\lambda^F_{rt}, x_{rt}\right)}{Cov\left(\Delta l_{rt}, x_{rt}\right)}\right] \approx \frac{\gamma^F \bar{\mu}^F}{\gamma^I \mu^I}\left[1 + \theta \sum_{i>0} \frac{Cov\left(x_{rt}, x_{rt-i}\right)}{Var\left(x_{rt}\right)}\right] \tag{35}$$

Recall the Table 2 estimates imply a mean foreign share of 38%, much larger than the 10% share of gross migratory flows $\frac{\bar{\mu}^F}{\mu^I}$. Can persistence in x_{rt} quantitatively account for the excess, without resorting to a large foreign elasticity, γ^F?

I only observe a short panel, so I impute the sum of autocorrelations of x_{rt} using estimated autoregressive processes. Since the coefficients on the employment variables in (16) are identical to those in the semi-structural equation (15), I can impute values for x_{rt} using:

$$x_{rt} = \delta_2 \Delta \tilde{n}_{rt} + \delta_3 \left(\tilde{n}_{rt-1} - l_{rt-1}\right) \tag{36}$$

where I set $\delta_2 = 0.743$ and $\delta_3 = 0.556$, based on column 2 of Table 7. In Table 9, I then estimate AR(1) and AR(2) processes for my imputed x_{rt} values, controlling for the amenity and year effects. Variation in x_{rt} may of course be conflated with omitted supply shocks. In an attempt to exclude these effects, I also offer IV estimates - where I instrument x_{rt-1} and x_{rt-2} with once and twice lagged Bartiks respectively. Since x_{rt} contains a dynamic term, even i.i.d. $\Delta \tilde{n}_{rt}$ shocks will generate some persistence.

But given the large population response (Panel A of Figure 3), this persistence will be relatively weak. So, serial correlation in $\Delta\tilde{n}_{rt}$ itself will be crucial.

Columns 5-6 suggest that x_{rt} follows a higher order process - unsurprisingly, given the dynamic term in (36). For AR(2), the implied sum of autocorrelations (reported in the table) is about 4 for OLS and 10 for IV. See Appendix B.7 for derivations of these sums. Calibrating θ to 0.469 (based on Table 8) and assuming equal foreign and internal elasticities ($\gamma^F = \gamma^I$), equation (35) then yields foreign shares of the population response of 32% (based on the OLS estimate) and 62% (based on IV). This suggests the estimated persistence in local shocks is sufficient to generate the observed 38% foreign share.

7 Conclusion

The US suffers from large and persistent local disparities in employment rates. Can immigration offer a remedy? Remarkably, I find that new immigrants account for 40% of the local population response to employment shocks. The effect is very general: I estimate a substantial foreign contribution in both high and low educated markets, driven by immigrants from diverse origins. However, it greatly exceeds their contribution to gross migratory flows (just 10%). Empirically, the excess response is almost entirely explained by spatial correlation between migrant enclaves and strong employment conditions. I attribute this correlation to a local snowballing effect, driven by persistent local shocks and the dynamics of migrant enclaves. I confirm the quantitative importance of this mechanism through calibration.

Despite this, foreign inflows do not significantly accelerate population adjustment, as they crowd out the contribution of internal mobility. Based on the model, this effect is too large to be driven by the labor market alone: the internal response to foreign inflows is significantly larger than its response to local employment shocks. Native distaste for migrant enclaves may play a role. Still, irrespective of the extent of crowd-out, a large foreign response will benefit natives (conditional on the overall level of immigration) if it saves them from incurring moving costs themselves. This can also help account for the secular decline in regional mobility in recent decades. And it raises concerns about policies which restrict asylum seekers' region of residence.

These results raise challenges to the (pervasive) application of enclaves as instruments for local migration shocks. But rather than abandoning the instrument, I offer an empirical strategy to overcome these challenges in general settings - in the absence of well-defined natural experiments. Based on my model, controlling for the initial employment rate (itself suitably instrumented) allows me to partial out the full history of both local demand and migration shocks. I present evidence that this "sufficient statistic" approach can address some of the principal threats to identification discussed in the migration literature.

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A Logit model of residential choice

A.1 Internal migratory flows

In this appendix, I set out a logit model of residential choice with idiosyncratic local preferences (building on e.g. McFadden, 1978, Monras, 2015, and Diamond, 2016). The intent is to motivate the equations for the rate of net internal inflows, λ_r^I, and foreign inflows, λ_r^I: i.e. (7) and (8) respectively. I begin by studying internal migratory flows, and I turn to foreign inflows in the next section.

For worker i, the value of living in area r is:

$$v_{ir} = \gamma^I v_r + \varepsilon_{ir} \tag{A1}$$

where v_r is a local fixed effect common to all workers (which will include the wage); and ε_{ir} is a logistically distributed i.i.d. taste shock. With arrival rate ζ^I, workers draw πL_s independent taste shocks from every area s (where L_s is local population) and choose their most preferred match. Thus, ε_{ir} in area r can be interpreted as the maximum of πL_s independent ε draws. This assumption can be motivated by a concept of network size: workers are more likely to meet a contact (offering a good local match) in larger areas.

Relative to local population, the net internal flow of workers to area r is then:

$$\begin{aligned} \lambda_r^I &= \zeta^I \left(\frac{L_r \exp \gamma^I v_r}{\sum_s L_s \exp \gamma^I v_s} \cdot \frac{\sum_{s \neq r} L_s}{L_r} - \frac{\sum_{s \neq r} L_s \exp \gamma^I v_s}{\sum_s L_s \exp \gamma^I v_s} \right) \\ &= \zeta^I \frac{\sum_{s \neq r} L_s \left(\exp \gamma^I v_r - \exp \gamma^I v_s \right)}{\sum_s L_s \exp \gamma^I v_s} \end{aligned} \tag{A2}$$

In the first line, the first term represents the inflow to area r, and the second term represents the outflow. The inflow term is multiplied by $\sum_{s \neq r} L_s$ (as workers arrive from multiple locations) and divided by L_r (to express it relative to local population). Now, taking a first order approximation of λ_r^I around a long run equilibrium with $v_s = \bar{v}$ in all areas s:

$$\begin{aligned} \lambda_r^I &\approx \frac{d\lambda_r^I}{dv_r} \Big|_{v_s = \bar{v}} \left(v_r - \bar{v} \right) \\ &= \gamma^I \mu_r^I \left(v_r - \bar{v} \right) \end{aligned} \tag{A3}$$

where μ_r^I is the steady-state migration rate out of area r:

$$\mu_r^I = \zeta^I \left(1 - \frac{L_r}{\sum_s L_s} \right) \tag{A4}$$

In an economy with many areas, μ_r^I will vary little with r. So, (A3) will then approximate to equation (7) in the main text, with $\mu^I \approx \zeta^I$.

As an aside, if there are indeed many areas (such that $\mu^I \approx \zeta^I$), the bulk of local adjustment is driven by changes in migratory inflows rather than outflows. This is in fact consistent with existing evidence (see e.g. Coen-Pirani, 2010; Monras, 2015; Dustmann, Schoenberg and Stuhler, 2017; Amior and Manning, 2018; Amior, 2020); and Monras (2015) uses the same assumptions to derive this result theoretically.

A.2 Foreign inflows

Suppose there is a constant inflow ζ^{Fo} of workers to the US from origin country o. On arrival, workers choose their most preferred location. Similarly to internal migrants, they sample multiple taste shocks from each area. But in this case, the sampling is proportional to the number of co-patriots (of origin o) in each area, L_{or}. As before, this assumption can be motivated by network size: origin o migrants are more likely to have contacts (who can help with absorption or job search) in areas with larger L_{or}. Utility in area r is given by:

$$v_{ir}^F = \gamma^F v_r + \varepsilon_{ir} \tag{A5}$$

where ε_{ir} is the maximum draw in each area r. Relative to local population, the total foreign inflow is then:

$$\lambda_r^F = \sum_0 \left(\frac{L_{or} \exp \gamma^F v_r}{\sum_s L_{os} \exp \gamma^F v_s} \cdot \frac{\zeta^{Fo}}{L_r} \right) \tag{A6}$$

where I have summed over all origin groups o. Consider a long run equilibrium with $v_s = \bar{v}$ in all areas s. Relative to local population, the steady-state foreign inflow to area r (i.e. the "foreign intensity") is then:

$$\mu_r^F = \frac{1}{L_r} \sum_0 \frac{L_{or}}{\sum_s L_{os}} \zeta^{Fo} \tag{A7}$$

Notice this is approximately equal to the enclave shift-share instrument described in equation (26), which I use to proxy the foreign intensity.

Finally, taking a first order approximation of λ_r^F around this long run equilibrium with $v_s = \bar{v}$:

$$\begin{aligned} \lambda_r^F &\approx \mu_r^F + \frac{d\lambda_r^F}{dv_r} |_{v_s=\bar{v}} (v_r - \bar{v}) \\ &= \mu_r^F + \frac{\gamma^F}{L_r} \sum_0 \left(1 - \frac{L_{or}}{\sum_s L_{os}}\right) \frac{L_{or}}{\sum_s L_{os}} \zeta^{Fo} (v_r - \bar{v}) \end{aligned} \tag{A8}$$

And if L_{or} is small compared to $\sum_s L_{os}$, this can be approximated by:

$$\lambda_r^F \approx \mu_r^F \left[1 + \gamma^F (v_r - \bar{v})\right] \tag{A9}$$

which yields equation (8) in the main text. Once migrants enter the US, I assume they behave identically to existing residents - as described in the previous section. That is, the utility weight on v_r in (A5) changes from γ^F to γ^I, and they sample taste shocks identically to existing residents - that is, proportional to total (rather than co-patriot) local population.

B Theoretical derivations

B.1 Moving to discrete time: Derivation of (11)

Here, I show how equation (9) can be discretized to yield (11). I assume the foreign intensity μ_r^F to area r is constant within discrete time intervals, and I denote μ_{rt}^F as the foreign intensity in the interval $(t-1,t]$. Similarly, γ_{rt} is the aggregate elasticity in area r in the interval $(t-1,t]$, where:

$$\gamma_{rt} = \gamma^I \mu^I + \gamma^F \mu_{rt}^F \tag{A10}$$

Now, let $x_r(\tau)$ denote the value of some variable x in area r at time τ. Notice that (9) can be written as:

$$\frac{\partial e^{\gamma_{rt}t} l_r(\tau)}{\partial \tau}|_{\tau=t} = e^{\gamma_{rt}t}\mu_{rt}^F + \gamma_{rt}e^{\gamma_{rt}t}\left[n_r(t) - z_r^{sa}(t)\right] \tag{A11}$$

This has as a solution:

$$e^{\gamma_{rt}t} l_r(t) = l_r(t-1) + \int_{t-1}^{t} e^{\gamma_{rt}\tau}\left[\mu_{rt}^F + \gamma_{rt}n_r(\tau) - \gamma_{rt}z_r^{\tau a}(\tau)\right] d\tau \tag{A12}$$

Rearranging:

$$\begin{aligned} l_r(t) - l_r(t-1) &= \int_{t-1}^{t} e^{-\gamma_{rt}(t-\tau)}\left[\mu_{rt}^F + \gamma_{rt}n_r(\tau) - \gamma_{rt}n_r(t-1) - \gamma_{rt}z_r^{\tau a}(\tau)\right] d\tau \\ &\quad + \left(1 - e^{-\gamma_{rt}t}\right)\left[n_r(t-1) - l_r(t-1)\right] \end{aligned} \tag{A13}$$

and again:

$$\begin{aligned} l_r(t) - l_r(t-1) &= \int_{t-1}^{t} e^{-\gamma_{rt}(t-\tau)} d\tau \cdot \mu_{rt}^F + \left[n_r(t) - n_r(t-1)\right] \\ &\quad - \left[z_r^{sa}(t) - z_r^{sa}(t-1)\right] - \int_{t-1}^{t} e^{\gamma_{rt}(\tau-t)}\left[\dot{n}_r(\tau) - \dot{z}_r^{sa}(\tau)\right] d\tau \\ &\quad + \left(1 - e^{-\gamma_{rt}t}\right)\left[n_r(t-1) - l_r(t-1) - z_r^{sa}(t-1)\right] \end{aligned} \tag{A14}$$

Assuming employment n_r and the supply/amenity shifter z_r^{sa} change at a constant rate over the interval, this yields:

$$\begin{aligned} l_r(t) - l_r(t-1) &= \left(\frac{1-e^{-\gamma_{rt}}}{\gamma_{rt}}\right)\mu_{rt}^F \\ &+ \left(1 - \frac{1-e^{-\gamma_{rt}}}{\gamma_{rt}}\right)\left[n_r(t) - n_r(t-1) - z_r^{sa}(t) + z_r^{sa}(t-1)\right] \\ &+ \left(1-e^{-\gamma_{rt}t}\right)\left[n_r(t-1) - l_r(t-1) - z_r^{sa}(t-1)\right] \end{aligned} \tag{A15}$$

which is (11).

B.2 Linearized foreign response to μ_{rt}^F: Derivation of (12)

Using (7) and (8), the discrete-time foreign contribution, λ_{rt}^F, can be expressed as:

$$\lambda_{rt}^F = \frac{\gamma^F \mu_{rt}^F}{\gamma_{rt}}\left(\Delta l_{rt} - \mu_{rt}^F\right) \tag{A16}$$

and after substituting (11) for Δl_{rt}:

$$\lambda_{rt}^F = \mu_{rt}^F + \frac{\gamma^F \mu_{rt}^F}{\gamma_{rt}}\left[\left(1 - \frac{1-e^{-\gamma_{rt}}}{\gamma_{rt}}\right)\left(\Delta n_{rt} - \Delta z_{rt}^{sa} - \mu_{rt}^F\right) + \left(1-e^{-\gamma_{rt}}\right)\left(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa}\right)\right] \tag{A17}$$

I now characterize this as a function f of μ_{rt}^F:

$$\begin{aligned} f\left(\mu_{rt}^F\right) &= \mu_{rt}^F + \frac{\gamma^F \mu_{rt}^F}{\gamma^I \mu^I + \gamma^F \mu_{rt}^F}\left(1 - \frac{1-e^{-\gamma^I \mu^I - \gamma^F \mu_{rt}^F}}{\gamma^I \mu^I + \gamma^F \mu_{rt}^F}\right)\left(\Delta n_{rt} - \Delta z_{rt}^s - \mu_{rt}^F\right) \\ &+ \frac{\gamma^F \mu_{rt}^F}{\gamma^I \mu^I + \gamma^F \mu_{rt}^F}\left(1 - e^{-\gamma^I \mu^I - \gamma^F \mu_{rt}^F}\right)\left(n_{t-1} - l_{t-1} - z_{rt-1}^s\right) \end{aligned} \tag{A18}$$

where I have replaced the aggregate elasticity γ^{rt} with $\gamma^I \mu^I + \gamma^F \mu_{rt}^F$. Taking a first order approximation around $\mu_{rt}^F = 0$ gives:

$$f\left(\mu_{rt}^F\right) \approx f(0) + \mu_{rt} f'(0) \tag{A19}$$

which yields:

$$\lambda_{rt}^F \approx \mu_{rt}^F + \frac{\gamma^F \mu_{rt}^F}{\gamma^I \mu^I}\left[\left(1 - \frac{1-e^{-\gamma^I \mu^I}}{\gamma^I \mu^I}\right)\left(\Delta n_{rt} - \Delta z_{rt}^{sa}\right) + \left(1 - \gamma^I \mu^I\right)\left(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa}\right)\right] \tag{A20}$$

which is equation (12) in the main text.

B.3 Derivation of semi-structural equation (15)

Assuming foreign intensity μ_{rt}^F is constant within the $(t-1, t]$ interval, the same must be approximately true of the foreign contribution λ_{rt}^F if employment shocks are small: see equation (A17). Following the procedure outlined in Appendix B.1, (14) can then be discretized to yield:

$$\Delta l_{rt} \approx \lambda_{rt}^F + \left(1 - \frac{1-e^{-\gamma^I \mu^I}}{\gamma^I \mu^I}\right)\left(\Delta n_{rt} - \lambda_{rt}^F - \Delta z_{rt}^{sa}\right) + \left(1 - e^{-\gamma^I \mu^I}\right)\left(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa}\right) \tag{A21}$$

Equation (15) then follows after subtracting the foreign contribution λ_{rt}^F on both sides:

$$\lambda_{rt}^I \approx \left(1 - \frac{1-e^{-\gamma^I \mu^I}}{\gamma^I \mu^I}\right)\left(\Delta n_{rt} - \lambda_{rt}^F - \Delta z_{rt}^{sa}\right) + \left(1 - e^{-\gamma^I \mu^I}\right)\left(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa}\right) \tag{A22}$$

B.4 Linearized population response to μ_{rt}^F: Derivation of (13)

Substituting (A20) for λ_{rt}^F in the semi-structural equation (A22) gives:

$$\begin{aligned} \lambda_{rt}^I \quad \approx \quad & -\left(1 - \frac{1-e^{-\gamma^I \mu^I}}{\gamma^I \mu^I}\right)\mu_{rt}^F + \left[1 - \frac{\gamma^F \mu_{rt}^F}{\gamma^I \mu^I}\left(1 - \frac{1-e^{-\gamma^I \mu^I}}{\gamma^I \mu^I}\right)\right]\left(1 - \frac{1-e^{-\gamma^I \mu^I}}{\gamma^I \mu^I}\right)\left(\Delta n_{rt} - \Delta z_{rt}^{sa}\right) \\ & + \left[1 - \frac{\gamma^F \mu_{rt}^F}{\gamma^I \mu^I}\left(1 - \frac{1-e^{-\gamma^I \mu^I}}{\gamma^I \mu^I}\right)\right]\left(1 - e^{-\gamma^I \mu^I}\right)\left(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa}\right) \end{aligned} \tag{A23}$$

To derived a linearized expression for the aggregate population change (i.e. (13) in the main text), I then take the sum of (A20) and (A23):

$$\begin{aligned} \Delta l_{rt} \quad \approx \quad & \frac{1-e^{-\gamma^I \mu^I}}{\gamma^I \mu^I}\mu_{rt}^F + \left(1 + \frac{\gamma^F \mu_{rt}^F}{\gamma^I \mu^I} \cdot \frac{1-e^{-\gamma^I \mu^I}}{\gamma^I \mu^I}\right)\left(1 - \frac{1-e^{-\gamma^I \mu^I}}{\gamma^I \mu^I}\right)\left(\Delta n_{rt} - \Delta z_{rt}^{sa}\right) \\ & + \left(1 + \frac{\gamma^F \mu_{rt}^F}{\gamma^I \mu^I} \cdot \frac{1-e^{-\gamma^I \mu^I}}{\gamma^I \mu^I}\right)\left(1 - e^{-\gamma^I \mu^I}\right)\left(n_{rt-1} - l_{rt-1} - z_{rt-1}^{sa}\right) \end{aligned} \tag{A24}$$

B.5 Foreign share of local adjustment: Derivation of (17)

Equation (17) is the foreign share of local population adjustment to composite employment shocks (as summarized by x_{rt} in (16)), taking the foreign intensity μ_{rt}^F as given. The foreign response to x_{rt} can be expressed as $\frac{Cov\left(\lambda_{rt}^F, x_{rt}\right)}{Var(x_{rt})}$ and the aggregate population response as $\frac{Cov(\Delta l_{rt}, x_{rt})}{Var(x_{rt})}$. So, the foreign share of the aggregate response is the ratio

$\frac{Cov\left(\lambda^F_{rt},x_{rt}\right)}{Cov(\Delta l_{rt},x_{rt})}$. Using (A20) and (A24), this can be expressed as:

$$\frac{Cov\left(\lambda^F_{rt},x_{rt}\right)}{Cov\left(\Delta l_{rt},x_{rt}\right)}=\frac{\frac{\gamma^F\mu^F_{rt}}{\gamma^I\mu^I}Var\left(x_{rt}\right)+\left(1+\frac{\gamma^F}{\gamma^I\mu^I}x_{rt}\right)Cov\left(\mu^F_{rt},x_{rt}\right)}{\left(1+\frac{\gamma^F\mu^F_{rt}}{\gamma^I\mu^I}\cdot\frac{1-e^{-\gamma^I\mu^I}}{\gamma^I\mu^I}\right)Var\left(x_{rt}\right)+\left(\frac{1-e^{-\gamma^I\mu^I}}{\gamma^I\mu^I}+\frac{1-e^{-\gamma^I\mu^I}}{\gamma^I\mu^I}\cdot\frac{\gamma^F}{\gamma^I\mu^I}x_{rt}\right)Cov\left(\mu^F_{rt},x_{rt}\right)} \tag{A25}$$

For small employment shocks x_{rt}, this can be approximated as:

$$\frac{Cov\left(\lambda^F_{rt},x_{rt}\right)}{Cov\left(\Delta l_{rt},x_{rt}\right)}\approx\frac{\frac{\gamma^F\mu^F_{rt}}{\gamma^I\mu^I}Var\left(x_{rt}\right)+Cov\left(\mu^F_{rt},x_{rt}\right)}{\left(1+\frac{\gamma^F\mu^F_{rt}}{\gamma^I\mu^I}\cdot\frac{1-e^{-\gamma^I\mu^I}}{\gamma^I\mu^I}\right)Var\left(x_{rt}\right)+\frac{1-e^{-\gamma^I\mu^I}}{\gamma^I\mu^I}Cov\left(\mu^F_{rt},x_{rt}\right)} \tag{A26}$$

And taking expectations over space and time:

$$\begin{aligned}\mathbb{E}\left[\frac{Cov\left(\lambda^F_{rt},x_{rt}\right)}{Cov\left(\Delta l_{rt},x_{rt}\right)}\right] &\approx \frac{\frac{\gamma^F\bar{\mu}^F}{\gamma^I\mu^I}Var\left(x_{rt}\right)+Cov\left(\mu^F_{rt},x_{rt}\right)}{\left(1+\frac{\gamma^F\bar{\mu}^F}{\gamma^I\mu^I}\cdot\frac{1-e^{-\gamma^I\mu^I}}{\gamma^I\mu^I}\right)Var\left(x_{rt}\right)+\frac{1-e^{-\gamma^I\mu^I}}{\gamma^I\mu^I}Cov\left(\mu^F_{rt},x_{rt}\right)}\\ &= \left[\left(\frac{\gamma^F\bar{\mu}^F}{\gamma^I\mu^I}+\frac{Cov\left(\mu^F_{rt},x_{rt}\right)}{Var\left(x_{rt}\right)}\right)^{-1}+\frac{1-e^{-\gamma^I\mu^I}}{\gamma^I\mu^I}\right]^{-1}\end{aligned} \tag{A27}$$

where $\bar{\mu}^F$ is the mean foreign intensity. This is equation (17) in the main text.

B.6 Projection of foreign intensity on x_{rt}: Derivation of (34)

I now derive an expression for $\frac{Cov\left(\mu^F_{rt},x_{rt}\right)}{Var(x_{rt})}$, the linear projection of foreign intensity μ^F_{rt} on the composite employment shock x_{rt}. Substituting the linearized foreign response (A20) for λ^F_{rt-1} into the equation for foreign intensity (33), I can write the evolution of μ^F_{rt} as:

$$\mu^F_{rt}=\mu^F_{rt-1}+\theta\frac{\gamma^F\mu^F_{rt-1}}{\gamma^I\mu^I}\left[\left(1-\frac{1-e^{-\gamma^I\mu^I}}{\gamma^I\mu^I}\right)\left(\Delta n_{rt-1}-\Delta z^{sa}_{rt-1}\right)+\left(1-e^{\gamma^I\mu^I}\right)\left(n_{rt-2}-l_{rt-2}-z^{sa}_{rt-2}\right)\right] \tag{A28}$$

where the expression in square brackets is the lagged composite employment shock, x_{rt-1}, as defined by (16):

$$\mu^F_{rt}=\mu^F_{rt-1}\left(1+\theta\frac{\gamma^F}{\gamma^I\mu^I}x_{rt-1}\right) \tag{A29}$$

Given its unit root, employment shocks have a permanent effect on μ^F_{rt}. Simulating backward:

$$\mu^F_{rt}=\bar{\mu}^F\prod_{i=1}^{\infty}\left(1+\theta\frac{\gamma^F}{\gamma^I\mu^I}x_{rt-i}\right) \tag{A30}$$

and taking a linear approximation for small employment shocks x_{rt}:

$$\mu^F_{rt}\approx\bar{\mu}^F\left[1+\theta\frac{\gamma^F}{\gamma^I\mu^I}\left(L+L^2+...\right)x_{rt}\right] \tag{A31}$$

where L is the lag operator, and $\bar{\mu}^F$ is the mean foreign intensity. A linear projection of foreign intensity μ_{rt}^F on the current composite employment shock x_{rt} then gives:

$$\frac{Cov\left(\mu_{rt}^F, x_{rt}\right)}{Var\left(x_{rt}\right)} \approx \theta \frac{\gamma^F \bar{\mu}^F}{\gamma^I \mu^I} \sum_{i>0} \frac{Cov\left(x_{rt}, x_{rt-i}\right)}{Var\left(x_{rt}\right)} \tag{A32}$$

which is equation (34).

B.7 Sum of autocorrelations for Table 9

In Table 9, I impute the infinite sum of autocorrelations of composition-adjusted employment shocks x_{rt}, based on the estimates of AR(1) and AR(2). In this appendix, I show how this is done.

Consider first an AR(1) process:

$$x_{rt} = \psi x_{rt-1} + u_{rt} \tag{A33}$$

where the error u_{rt} is i.i.d. The ith autocorrelation is simply ψ^i, so the sum of autocorrelations is:

$$\sum_{i>0} \frac{Cov\left(x_{rt}, x_{rt-i}\right)}{Var\left(x_{rt}\right)} = \frac{\psi}{1-\psi} \tag{A34}$$

Now consider an AR(2) process:

$$x_{rt} = \psi_1 x_{rt-1} + \psi_2 x_{rt-2} + u_{rt} \tag{A35}$$

Let m_1^{-1} and m_2^{-1} be the two roots of the associated characteristic equation, $1 - \psi_1 L - \psi_2 L^2 = 0$. Stationarity is ensured by the condition: $|m_k| < 1$ for $k = 1, 2$, where the m_k are inverses of the roots. Fuller (1996, p. 56) shows that the ith autocorrelation is given by:

$$\frac{Cov\left(x_{rt}, x_{rt-i}\right)}{Var\left(x_{rt}\right)} = \frac{\left(1-m_2^2\right) m_1^{i+1} - \left(1-m_1^2\right) m_2^{i+1}}{\left(m_1 - m_2\right)\left(1 + m_1 m_2\right)} \tag{A36}$$

so the sum of autocorrelations is:

$$\sum_{i>0} \frac{Cov\left(x_{rt}, x_{rt-i}\right)}{Var\left(x_{rt}\right)} = \frac{\left(1-m_2^2\right) m_1^2 \left(1-m_1\right)^{-1} - \left(1-m_1^2\right) m_2^2 \left(1-m_2\right)^{-1}}{\left(m_1 - m_2\right)\left(1 + m_1 m_2\right)} \tag{A37}$$

C Data manipulation

C.1 Population

I take local population counts of individuals aged 16-64 from published county-level census statistics (based on 100% samples), extracted from the National Historical Geographic

Information System (NHGIS: Manson et al., 2017). See Table A1 of the Online Appendix of Amior and Manning (2018) for table references. Commuting Zones (CZs) are composed of groups of counties, in line with Tolbert and Sizer (1996). I make one modification to the Tolbert-Sizer scheme to facilitate construction of consistent geographies over time: I move La Paz County (AZ) to the same CZ as Yuma County (AZ). These counties only separated in 1983, but Tolbert and Sizer's 1990 scheme allocates them to different CZs.

I disaggregate the total population of 16-64s into native and foreign-born components using local shares computed from the Integrated Public Use Microdata Series (IPUMS: Ruggles et al., 2017) samples. I use this procedure to compute local counts for other demographic cells also: specifically, recent foreign-born arrivals (in the US for 10 years or less), longer term migrants, and these in turn (together with the native-born) disaggregated by education. In practice, the sub-state geographical identifiers included in the IPUMS microdata do not coincide with CZ boundaries, and these identifiers vary by census year.[27] Similarly to Autor and Dorn (2013) and Autor, Dorn and Hanson (2013), I estimate population counts at the intersection of the available geographical identifiers and CZs[28], and I impute CZ-level data using these counts as weights.

I use the following IPUMS samples for this exercise: the American Community Surveys (ACS) of 2009, 2010 and 2011 (pooled together) for the 2010 cross-section; the 5 per cent census extracts for 2000, 1990, 1980 and 1960; and the (pooled) forms 1 and 2 metro samples of 1970 (each of which are 1 per cent extracts). Regarding 1970, information on years in the US is only available in the form 1 sample.

C.2 Employment

In this section, I describe in greater detail how I construct composition-adjusted local employment rates. I begin by running probit regressions of individual employment on detailed demographic characteristics (see below) and area fixed effects, separately for each census cross-section (1960, 1970, 1980, 1990 and 2000) and the pooled ACS cross-sections of 2009-11. For the fixed effects, I use the finest indicators for local geographies available

[27] The 1950 census extract (which I require for the lagged instruments) divides the continental US into 467 State Economic Areas, the 1960 extract uses 2,287 "Mini" Public Use Microdata Areas (PUMAs), the 1970 extracts (the forms 1 and 2 metro samples) use 405 county groups, 1980 uses 1,148 county groups, 1990 uses 1,713 PUMAs, and the 2000 census extract and American Community Survey (until 2011) use 2,057 PUMAs.

[28] Following Amior and Manning (2018), I use county-SEA lookup tables from IPUMS (*https://usa.ipums.org/usa/resources/volii/ sea_county_components.xls*) for 1950 (which I require for the lagged instruments); and I use county group lookup tables from IPUMS for 1970 and 1980 (*https://usa.ipums.org/usa/resources/volii/1970cgcc.xls* and *https://usa.ipums.org/usa/resources/volii/cg98stat.xls*). For 1960, I rely on a preliminary lookup table linking Mini PUMAs to counties (with population counts at the intersections), kindly shared by Joe Grover at IPUMS. And for the 1990 and 2000 PUMAs, I generate population counts using the MABLE/Geocorr applications at the Missouri Census Data Center: *http://mcdc.missouri.edu/websas/geocorr_index.shtml*.

in each census year (see Section C.1). These are demanding specifications: to reduce the number of fixed effects in the probit regressions as much as possible, I aggregate together geographical units which are subsumed within the same CZs.

I then compute composition-adjusted employment rates, $\tilde{ER}_{rt}$, by taking the mean predicted employment rate in each area r for a distribution of local demographics identical to the full national sample:

$$\tilde{ER}_{rt} = \int_i \Omega \left(X_{it}\hat{\theta}_t + \hat{\theta}_{rt} \right) g \left(X_{it} \right) di \tag{A38}$$

where Ω is the normal c.d.f., $\hat{\theta}_t$ is the vector of estimated probit coefficients on the individual characteristics, $\hat{\theta}_{rt}$ are the probit area fixed effects, and $g \left(X_{it} \right)$ is the national-level density of individuals with characteristics X_{it}. I then impute composition-adjusted employment rates at the CZ level by taking weighted averages (across the available geographical units), using the population weights described in Section C.1.

The individual controls in the probit regressions consist of: age and age squared; four education indicators[29], each interacted with age and age squared; a gender dummy, interacted with all previously-mentioned variables; black/Asian/Hispanic indicators, interacted with all previously-mentioned variables; and a foreign-born indicator, interacted with all previously-mentioned variables. And finally, to the extent that it is possible in each cross-section, I control for years in the US (among the foreign-born), again interacted with all previously-mentioned variables. This information is not consistently reported in each cross-section, so the variables I use vary by year:

ACS 2009-11: Years in US, years in US squared.

Census 2000: Years in US, years in US squared.

Census 1990: The census only reports years in US as a categorical variable. I take the mid-point of each category (and its square), and I also include a dummy for top-category cases.

Census 1980: Same as 1990. Except those who were citizens at birth do not report years in US: I code all these cases with a dummy variable.

Census 1970: Same as 1980. Except some respondents do not report years in US: I code all these non-response cases with a dummy variable. I also include an additional binary indicator for migrants who report living abroad five years previously (based on a different census question), which is available for the full sample.

Census 1960: No information on years in US is available.

All these variables (relating to years in US) are interacted with all previously-mentioned variables in the probit specification. For the 1970 specification, I exclude foreign-born

[29]High school graduate (12 years of education), some college education (1 to 3 years of college), undergraduate degree (4 years of college) and postgraduate degree (more than 4 years of college). High school dropouts (less than 12 years of education) are the omitted category.

individuals in the form 2 sample, since these do not report years in the US.

C.3 Shift-share variables

The sample for the Bartik industry shift-shares is based on employed individuals aged 16-64 in the IPUMS census extracts and ACS samples. I identify industries using the IPUMS consistent classification based on the 1950 census scheme[30], aggregated to the 2-digit level[31] (with 57 codes). As with the population counts (see above), I impute CZ-level employment counts (by industry) by weighting data from the corresponding sub-state geographical identifiers.

Similarly, in the construction of the enclave shift-share $\hat{\mu}_{rt}^F$, I impute CZ-level migrant population counts (across 77 origin countries) by weighting across these same identifiers. A key input to $\hat{\mu}_{rt}^F$ is the number of new migrants (by origin o) arriving in the US in the previous ten years (and residing outside area r): i.e. $L_{o(-r)t}^F$ in equation (26) in Section 3.4. This information is available in all census years from 1970 inclusive, thus covering foreign inflows from the 1960s onward. However, for columns 5-7 of Table 7, I require values of $\hat{\mu}_{rt}^F$ for 1960 (covering the 1950s inflow). For that decade, I impute foreign inflows using cohort changes: I compute the difference between (i) the stock of migrants of origin o in 1960 (outside area r) and (ii) the stock of migrants of origin o in 1950 aged 6-54 (again, outside r).

C.4 Data for Figure 1

This section describes the data I use to put together Figure 1. The estimates are mostly based on the March waves of the IPUMS Current Population Survey (Flood et al., 2018). The sample consists of individuals aged 16 to 64 between 1964 and 2018. Following the recommendation of Kaplan and Schulhofer-Wohl (2012), I also exclude observations with imputed migration status: there are inconsistencies in the CPS's imputation procedure.

Panel A describes trends in annual gross migratory flows to US states. The "internal" flow is the share of individuals living in a different state (within the US) 12 months previously. The "foreign" flow is the share of individuals who are (i) foreign-born and (ii) living abroad 12 months previously. The "recent immigrant" flow is the share of individuals who are (i) foreign-born with no more than five years in the US and (ii) living outside their current state 12 months previously (either in a different state or abroad). Panel B reports the share of total gross flows to US states (i.e. all individuals living outside their current state 12 months previously) which are due to foreign-born individuals coming from abroad: i.e. the ratio of "foreign" to total inflows.

[30] See *https://usa.ipums.org/usa/volii/occ_ind.shtml.*

[31] I further aggregate all wholesale sectors to a single category to address inconsistencies between census extracts, and similarly for public administration and finance/insurance/real estate. I also omit the "Not specified manufacturing industries" code.

Migration status is not reported in certain years of the March CPS (specifically 1972-5, 1977-80, 1985 and 1995), and I interpolate linearly in these cases. This is sufficient to produce my internal flow series in Panel A.

However, the foreign inflow presents greater challenges. Unfortunately, country of birth is not reported before 1994 - so I cannot distinguish between native and foreign-born status in these years. An alternative data source is the US census, but it only provides information on place of residence 5 years (and not 12 months) previously. My strategy is to impute the annual foreign inflow using the 5-year foreign inflow (i.e. the share of individuals who are foreign-born and living abroad 5 years previously), estimated at decadal intervals in the census. I proceed with the following steps. (1) I compute the mean annual foreign inflow in the CPS over 1996-2000, and I also compute the 5-year foreign inflow in the 2000 census. (2) I compute the ratio of these: the latter is 5.3 times the former.[32] (3) I then impute the annual foreign inflow in 1988 (the mid-point of 1986-1990) by dividing the 5-year inflow in the 1990 census by 5.3. And in the same way, I impute the 1978 annual foreign inflow using the 1980 census, and the 1968 foreign inflow using the 1970 census. (4) Finally, I linearly interpolate all missing observations, and I assume the foreign inflow over 1964-7 is the same as 1968.

D Years in US and geographical mobility

In this appendix, I offer some evidence on the gross mobility of natives and migrants within the US, based on American Community Survey (ACS) samples between 2000 and 2018. I have chosen to use the ACS for this exercise instead of the CPS because of larger samples and greater consistency (across survey years) in the categorization of years in the US (among foreign-born individuals).

In my ACS sample, 2.8% of native-born individuals aged 16-64 report living in a different state 12 months previously (conditional on living in the US at that time), compared to 2.4% of the foreign born. However, the foreign-born share masks some important heterogeneity by years in the US. In what follows, I show that new migrants are in fact more mobile across states than natives, but this differential is eliminated within five years.

To identify the effect of years in the US, it is important to control for entry cohort effects (Borjas, 1985) and observation year effects. To this end, I estimate complementary log-log models for the annual incidence of cross-state migration. Let $MigRate\left(X_i\right)$ denote the instantaneous cross-state migration rate conditional on a vector of individual characteristics X_i. An individual i moves between states over a time horizon τ with

[32]Theoretically, one would expect this ratio to be less than 5, to the extent that previous immigrants return home. But in practice, differences in sampling procedures (and response rates) are likely to play a role also. The advantage of my imputation method is that it accounts for any such (time-invariant) differences between CPS and census sampling.

probability:

$$\Pr\left(Mig_i^\tau = 1\right) = 1 - \exp\left(-MigRate\left(X_i\right)\tau\right) \tag{A39}$$

This gives rise to a complementary log-log model:

$$\Pr\left(Mig_i^\tau = 1\right) = 1 - \exp\left(-\exp\left(\pi' X_i\right)\tau\right) \tag{A40}$$

where the π parameters (to be estimated) are elasticities of the instantaneous migration rate $MigRate\left(X_i\right)$ with respect to the characteristics in X_i. Assuming a constant hazard, this interpretation of the π parameters is independent of the time horizon τ associated with the data. I define a cross-state migrant as somebody living in a different state 12 months previously (as reported by the ACS), so I normalize τ to one year. The X_i vector includes the following variables:

$$\pi' X_i = \sum_{k=1}^{20} \pi_k^{YRS} YrsUS_k + \sum_{k=1981}^{2017} \pi_k^{YRI} YrImmig_k + \sum_{k=2000}^{2018} \pi_k^{YRI} YrObs_k \tag{A41}$$

The sample for this exercise consists of (i) natives aged 16-64 living in the US one year previously (22.6m observations) and (ii) foreign-born individuals aged 16-64 with between 1 and 20 years in the US (2.8m). Thus, there are 21 demographic groups: natives, migrants with 1 years in US, migrants with 2 years, ..., migrants with 20 years. The $YrsUS_k$ are binary indicators for the final 20 groups (for k between 1 and 20), so natives are the omitted category. I also control for a full set of entry year cohort effects, $YrImmig_k$ (ranging from 1980 to 2017 in my sample; the omitted category is the 1980 cohort, as well as natives), and a full set of observation year effects, $YrObs_k$.

Panel A of Figure A1 reports the basic coefficient estimates on the years in US dummies, together with the 95% confidence intervals. The estimates can be interpreted as the log point difference in cross-state mobility between migrants (with given years in US) and natives, controlling for entry cohort and observation year effects. Migrants are initially more mobile than natives: the deviation at the entry year is 1.1 log points. But the gap becomes small after five years of entry, turns negative within ten, and drops to -0.3 log points by year 20.

It turns out that these patterns can partly be explained by differences in age: newer immigrants are typically younger, and younger people are more mobile. But even within age groups, the patterns look qualitatively similar. I present these results in Panel B, where I estimate the same empirical model - but this time controlling for a full set of single-year age effects. The deviation at year 1 is now much smaller (0.6 log points), and it reaches zero by year 5.

E Supplementary OLS, reduced form and first stage estimates

In this section, I present OLS and reduced form estimates corresponding to various tables in the main text.

Table A1 reports OLS and reduced form estimates for the average contributions to local population adjustment (corresponding to Table 2 in the main text). Table A2 repeats this exercise for the heterogeneity estimates (corresponding to Table 5).

Table A3 offers first stage estimates for the education-specific average contributions (corresponding to the IV estimates in Table 3). And Table A4 reports first stage estimates for the education-specific semi-structural specifications (i.e. columns 3-4 of Table 7).

F Robustness of IV contributions to local adjustment (Tables 2 and 5)

F.1 Robustness to specification

In Tables A5, A6 and A7, I study the robustness of my IV estimates of the foreign contribution to local adjustment. In columns 1-4 of each tables, I consider the robustness of the average contributions - corresponding to Table 2 in the main text. And in columns 5-8, I consider the heterogeneity in these contributions (and the crowd-out effect) along the enclave shift-share - corresponding to Table 5.

Table A5 focuses on the robustness to specification choices. For reference, Panel A reproduces the estimates from the main text: i.e. the average contributions in columns 2-5 of Table 2 (without the enclave shift-share control, $\hat{\mu}_{rt}^{F}$) and the heterogeneous contributions in columns 2-5 of Table 5.

In Panel B, in an effort to account for time-invariant unobserved components of supply/amenity effects in Δz_{rt}^{sa} and z_{rt-1}^{sa} in equation (11), I control for CZ fixed effects - which effectively partial out CZ-specific linear trends in population. The aggregate population response is larger, at least to the lagged employment rate (column 1); but the average foreign contribution to this response is almost entirely eliminated (column 2). This is perhaps to be expected: the fixed effects pick up much of the same variation as the enclave shift-share $\hat{\mu}_{rt}^{F}$ (which is locally very persistent); and Table 2 in the main text shows that controlling for $\hat{\mu}_{rt}^F$ also eliminates much of the foreign contribution. Having said that, the heterogeneous effects in columns 5-8 are not substantially affected: there remains a large foreign response in high-$\hat{\mu}_{rt}^F$ areas, which is (more than) fully crowded out by the residual contribution; though there is little crowd-out of the direct effect of $\hat{\mu}_{rt}^F$. It should be emphasized that this is a very demanding specification, given the short panel length (just five periods) and the four endogenous variables.

In Panel C of Table A5, I omit the lagged employment rate and its associated (lagged Bartik) instrument - together with their interactions with the enclave shift-share in columns 5-8. As one would expect (given serial correlation in the Bartik instrument), the response to the contemporaneous employment change (column 1) is now larger. The difference is substantial: compared to Panel A, the gap between the β_1 coefficient (on the change in current employment) and 1 (i.e. full adjustment) is halved. But the foreign contribution (column 2) is proportionately similar. And in columns 5-8, the foreign contribution continues to fully crowd out the internal contribution, at least in the response to employment shocks (i.e. the "indirect" effect).

Finally, Panel D uses raw instead of composition-adjusted employment variables, for both the contemporaneous change and the lagged rate. The aggregate population response in column 1 is now somewhat smaller. This result is intuitive. The local population of better educated workers is known to respond more strongly (see e.g. Amior and Manning, 2018), and these individuals also have higher employment rates. As a result, the change in raw employment (on the right hand side) overstates the true change in employment for an individual of fixed characteristics; and the population response to this change must therefore be smaller. Still, the foreign contribution in column 2 is proportionately similar; and columns 5-8 show a similar crowding out effect. This result should be reassuring: since adjusting local employment for observable demographic characteristics makes little difference to the results, one may be less concerned about the influence of unobservables.

F.2 Robustness to amenity controls

In Table A6, I study the robustness of my estimates to the right hand side controls. In Panel A, I control only for the full set of year effects - and exclude all amenity controls. The aggregate population response (column 1) is similar to the main text, and the foreign contribution (column 2) is proportionately larger - especially in response to the lagged employment rate, where it actually exceeds the aggregate response. The coefficients on the interaction terms in columns 5-8 continue to point to total crowd-out of the employment responses, though the standard errors are now very large: the interactions effects are statistically insignificant.

The same is true of Panel B, where I control for the basic amenity effects - but omit the interactions between the amenity effects and the enclave shift-share, $\hat{\mu}_{rt}^{F}$. The interactions with the employment effects in columns 5-8 are larger in magnitude, and the standard errors are smaller - but the effects are still insignificant at the 5% level. However, it should be emphasized that the omission of the amenity-$\hat{\mu}_{rt}^{F}$ controls is a misspecification: see equation (13) in the main text.

Panel C controls additionally for the amenity-$\hat{\mu}_{rt}^{F}$ interactions. Columns 5-8 are now identical to columns 2-5 of Table 5 in the main text, and the foreign contribution to the average response in column 2 is a little smaller than before. This reflects what happens in Table 2 in the main text when I control for the enclave shift-share, $\hat{\mu}_{rt}^{F}$.

F.3 Robustness to sample and weights

In Table A7, I vary the sample and weighting. Until now, I have studied local heterogeneity along the enclave shift-share, $\hat{\mu}_{rt}^{F}$: this follows the first order approximation imposed in equation (12) in the model. But as I note in the main text, the $\hat{\mu}_{rt}^{F}$ distribution is heavily skewed: the 98th percentile is 0.1, and the maximum is 0.29. In Panel A, I consider the implications of omitting observations with $\hat{\mu}_{rt}^{F}$ exceeding 0.1. As one would expect, the average foreign contribution in column 2 is somewhat smaller - at least in response to the lagged employment rate. But the heterogeneous effects in columns 5-8 are similar: we continue to see perfect crowd-out. This suggests the results are not driven by a small number of outlying observations of $\hat{\mu}_{rt}^{F}$, and the linear approximation may not be so unreasonable.

All the estimates in the main text are weighted by lagged population share. In Panel B of Table A7, I study unweighted estimates. This places more emphasis on smaller CZs which typically admit fewer immigrants. Unsurprisingly, the average foreign contribution is now substantially lower. Column 6 shows the foreign contribution is increasing with $\hat{\mu}_{rt}^{F}$, but the effect is smaller than before. However, there is now no crowd-out of the employment response in column 7. It turns out this result is driven by some small towns close to the Mexican border with unusually large migrant enclaves (which contribute little to the weighted estimates). Once I exclude CZs with 1960 population (of 16-64s) below 25,000 (which account for 2% of the national population), column 7 now shows evidence of crowd-out (though with very large standard errors). And the crowding out effect becomes effectively one-for-one (and much more precise) once I exclude CZs with 1960 population below 50,000. This exclusion removes the majority of CZs (387 out of 722), but these account for just 7% of the national population.

F.4 Isolating the mobility response of foreign-born residents

Columns 4-5 of Table 2 show that the total residual contribution, $\hat{\lambda}^I_{rt}$, to local adjustment is very similar to that of natives alone, $\hat{\lambda}^{I,N}_{rt}$. This indicates that "old" migrants (those living in the US since at least $t-1$) contribute little to adjustment. However, one may be concerned that this does not reflect their mobility response (whether internally or through emigration), but rather generational shifts between foreign-born residents and their native children. I now address this by studying within-cohort changes in population stocks.

In line with equations (19)-(21), I approximate the overall contribution of "old migrants" as:

$$\hat{\lambda}^{I,OM}_{rt} \equiv \log\left(\frac{L_{rt-1} + L^M_{rt} - L^M_{rt-1} - L^F_{rt}}{L_{rt-1}}\right) \tag{A42}$$

where L^M_{rt} is the population of all migrants (i.e. foreign-born individuals) aged 16-64 living in area r and period t; and L^F_{rt} is the foreign inflow, i.e. the stock of "new" immigrants in t (who arrived in the US in the previous ten years). I also define the within-cohort contribution of old migrants as:

$$\hat{\lambda}^{I,OM,cohort}_{rt} \equiv \log\left(\frac{L_{rt-1} + L^M_{rt} - L^{M,5-54}_{rt-1} - L^F_{rt}}{L_{rt-1}}\right) \tag{A43}$$

where $L^{M,5-54}_{rt-1}$ is the stock of migrants in $t-1$ aged 5-54. This latter variable keeps the cohort of migrants fixed, so changes in the area r stock can only be driven by internal mobility or emigration.

In Table A8, I re-estimate the IV regressions in Panels A and B of Table 2, but alternately replacing the dependent variable with the overall contribution of old migrants $\hat{\lambda}^{I,OM}_{rt}$ and the within-cohort contribution $\hat{\lambda}^{I,OM,cohort}_{rt}$. The results look very similar in each case: the response to employment shocks is small and statistically insignificant. This indicates that there is indeed little mobility response to employment shocks, whether through internal migration or emigration.

F.5 Average contributions by region of origin

One may be interested in whether the large foreign contribution identified in the main text is driven by migrants of particular origins. I address this question in Table A9. Column 1 reports the average IV foreign contribution (among all origins groups) - which is identical to column 3 of Table 2 in the main text, based on the empirical specification (27). And in the remaining columns, I replace the dependent variable with the (approximate) contribution from various origin groups: specifically $\hat{\lambda}_{rt}^{Fo} \equiv \log\left(\frac{L_{rt-1}+L_{rt}^{Fo}}{L_{rt-1}}\right)$, where L_{rt}^{Fo} is the stock of new migrants of origin o in area r at time t, who arrived in the US in the previous ten years.

All the origin groups contribute significantly to the overall foreign response. And none can be said to be particularly dominant, especially given the associated standard errors.

G Robustness of semi-structural estimates (Table 7)

G.1 Graphical illustration of crowding out estimates

I now consider the robustness of my "semi-structural" crowding out estimates in Table 7 (Section 5.3). One concern is that my estimates of the coefficient of interest, δ_1, in equation (29) may be driven by outliers. To address this point, Figure A2 graphically illustrates the basic OLS and IV estimates of δ_1, i.e. those of columns 1 and 2 of Table 7.

These plots follow the logic of the Frisch-Waugh theorem. For OLS, I compute residuals from regressions of both the residual and foreign contributions ($\hat{\lambda}_{rt}^{I}$ and $\hat{\lambda}_{rt}^{F}$ respectively) on the remaining controls: the employment change, lagged employment rate, year effects and the amenity variables (interacted with year effects). And I then plot the $\hat{\lambda}_{rt}^{I}$ residuals against the $\hat{\lambda}_{rt}^{F}$ residuals.

For the IV plot, I apply the Frisch-Waugh logic to two-stage least squares. I begin by generating predictions of the three endogenous variables (the foreign contribution $\hat{\lambda}_{rt}^{F}$, the employment change $\Delta\tilde{n}_{rt}$, and the lagged employment rate $\tilde{n}_{rt-1} - l_{rt-1}$), based on the first stage regressions (using the enclave shift-share $\hat{\mu}_{rt}^{F}$ and current and lagged Bartik instruments, b_{rt} and b_{rt-1}). I then compute residuals from regressions of both $\hat{\lambda}_{rt}^{I}$ and the *predicted* $\hat{\lambda}_{rt}^{F}$ on the remaining controls: the *predicted* employment change, the *predicted* lagged employment rate, year effects and the amenity variables (interacted with year effects). And as before, I plot the $\hat{\lambda}_{rt}^{I}$ residuals against the $\hat{\lambda}_{rt}^{F}$ residuals.

The marker size in the plots correspond to the lagged population share weights. The (weighted) slopes of the fit lines are identical to the δ_1 estimates in columns 1 and 2 in Table 7. Note the standard errors (of course) do not match: I do not account for state clustering in Figure A2; and for IV, the naive two stage estimator does not account for sampling error in the first stage. In any case, it is clear from inspection that the δ_1 estimates are not driven by outliers.

G.2 Robustness to sample, controls and weighting

In Table A10, I study the sensitivity of my basic IV estimate of δ_1 (in column 2 of Table 7) to the choice of controls, decadal sample and weighting. I begin, in Panel A, by weighting observations by lagged local population share - as I do in the main text. Without any controls, the estimates vary substantially over time: there is little crowd-out before 1990, but much more thereafter. This reflects the concerns of Borjas, Freeman and Katz (1997) on the instability of spatial correlations, and it offers a strong motivation for pooling many decades of data. As one might expect, the average δ_1 increases (from -0.53 to -0.75) when I control for the employment change and lagged employment rate (column 6); and it becomes much more stable across time. Controlling for the amenity effects raises the average effect further still (from -0.75 to -0.91), though there is now insufficient power to identify anything meaningful in the 1990s.

In Panel B, I repeat the exercise without observation weights. Interestingly, I now identify very positive values for δ_1 without controls. But once the full set of controls are included, the estimates become remarkably similar to those of Panel A. In particular, the pooled effect is 0.884 (without weights) compared to 0.913 (with weights), both with standard errors below 0.1. At least conditional on the employment and amenity controls, this suggests the crowding out effect is not markedly different in larger CZs. And it offers support for my empirical specification.

H Reconciliation with Cadena and Kovak (2016)

H.1 Summary

In important work, Cadena and Kovak (2016) study the contribution of (specifically Mexican) immigrants to local labor market adjustment; and like me, they exploit variation in historical settlement patterns. But, their results diverge from mine in three ways. (1) Cadena and Kovak find that low educated natives contribute negligibly to local adjustment - in contrast to Mexican-born workers. (2) They find that Mexicans respond heavily even after arriving in the US - while in my paper, the immigrant response is entirely driven by new arrivals. (3) They find that Mexicans substantially smooth local fluctuations in employment rates (more than halving the effect of local demand shocks), which appears to imply little crowd-out. Based on the intuition from my model, notice that the final claim follows theoretically from the first: migrants will only “grease the wheels” if the wheels are not already greased, i.e. if natives themselves contribute little to adjustment.

There are some differences in empirical setting. While Cadena and Kovak focus on the contribution of Mexican-born immigrants to local adjustment between 2006 and 2010 (during the Great Recession) across 94 Metropolitan Statistical Areas (MSAs)[33], I study the contribution of all immigrants across 722 CZs over a longer period (1960-2010).

But, I argue here that differences in empirical specification *alone* can account for the divergent results: once I account for dynamics, I find that the low educated native population does respond strongly to local shocks. Monras (2015) has also challenged the results of Cadena and Kovak: he attributes the weak native response to unobserved divergent trends in local native and Mexican populations. But I find that controlling for the initial employment rate (fully observed in the data), as my model requires, is sufficient to generate a much larger native response. The effect of dynamics is intuitive: as Cadena and Kovak note, those cities which suffered larger downturns during their Great Recession sample had enjoyed larger upturns earlier in the decade; and if adjustment is sluggish, local population movements over 2006-10 will reflect responses to both. The data reject the hypothesis that these dynamics are unimportant, just as in my 50-year dataset.

H.2 Empirical model

Cadena and Kovak base their main analysis on the following specification:

$$\Delta l_{gr} = \omega_{0g} + \omega_{1g} IndShock_{gr} + X_r \omega_{Xg} + \varepsilon_{gr} \tag{A44}$$

See equation (1) of their paper, though I have altered notation to match my own. The equation is estimated separately for nativity groups g: natives, Mexican migrants and non-Mexican migrants. The dependent variable Δl_{gr} is the 2006-10 change in log local population in a given nativity group, and $IndShock_{gr}$ is the contemporaneous within-industry employment shock experienced by that group. This is the weighted average of industry-specific employment changes:

$$IndShock_{gr} \equiv \sum_i \phi^i_{gr} \Delta n_{ir} \tag{A45}$$

where the weights ϕ^i_{gr} are initial group-specific shares of local workers employed in industry i. I focus specifically on their Table 4: there, Cadena and Kovak instrument $IndShock_{grt}$ using a contemporaneous Bartik industry shift-share (common to all nativity groups), akin to that described in equation (25) in the main text. The coefficient ω_{1g} is interpreted as the group-specific elasticity of population to a local group-specific demand shock. Two right-hand side controls are included in the vector X_r: the Mexican population share in 2000 and indicators for MSAs in states that enacted anti-migrant

[33] They restrict attention to MSAs with adult population exceeding 100,000, Mexican-born sample exceeding 60, and non-zero samples for all other studied demographic groups.

employment legislation. Like Cadena and Kovak, I weight all estimates using inverse sample variances.

Notice the conceptual framework here is different to mine. My approach, motivated by my model, is to study the overall population response to an aggregate-level shock, and I disaggregate this response into the contributions from various groups (new migrants, natives, old migrants). In contrast, equation (A44) estimates the elasticity of group-specific population stocks to group-specific employment shocks. Cadena and Kovak estimate that ω_{1g} is statistically insignificant for low educated natives, but large and positive for equivalently educated Mexican-born individuals. Given this, they argue that the aggregate low educated population will respond more strongly to a given employment shock in cities with larger Mexican enclaves; and therefore, these cities will suffer weaker fluctuations in local employment rates.

Beyond this, there are two further differences in the empirical specification. First, (A44) studies the response to a within-industry employment shock $IndShock_{gr}$, rather than a change in overall employment Δn_{gr} which accounts additionally for between-industry shifts. And most importantly, (A44) does not account for local dynamics.

H.3 Estimates

I explore the implications of the employment shock definition and dynamics in Table A11, relying on data and programs published alongside Cadena and Kovak's article. I restrict attention to non-college workers (and specifically men) - who account for Cadena and Kovak's headline results. Columns 1-4 of Panel A in Table A11 replicate Panel A of Table 4 in their paper. The response of non-college natives to local demand shocks (instrumented by a Bartik shift-share) is negligible, while the Mexican-born population responds heavily (with a one-for-one effect). The response of non-Mexican migrants is large and negative, offsetting much of the Mexican response. The overall population response (column 1) is positive but statistically insignificant.

In Panel B, I replace the within-industry employment shock $IndShock_{gr}$ with a simple change in (group-specific) log employment Δn_{gr} - though I continue to use the same Bartik instrument. The estimates are mostly unchanged, except we now see a large positive response from non-Mexican migrants.

In Panel C, I control additionally for the initial group-specific employment rate (i.e. in 2006), which I instrument using a Bartik industry shift-share for 2000-6.[34] The specification now has the form of an error correction model (ECM), regressing the change

[34]Cadena and Kovak construct this lagged Bartik for some robustness exercises in their own paper, so I take it from their dataset.

in (group-specific) log population on the change in (group-specific) log employment and the initial (group-specific) log employment rate. Since column 1 is based on the full population, it is essentially identical to my ECM specification in equation (11). But as I have already described, the group-specific responses (in the remaining columns) are not comparable: these represent group-specific elasticities, rather than contributions to aggregate adjustment.

Notice first that the effect of the initial employment rate is large (the elasticity of the overall population is 0.68) and statistically significant: that is, the data reject the hypothesis that the dynamics are unimportant. Also, the responses of the overall population (column 1) and natives (column 2) to the *contemporaneous* employment shock are now substantially larger, with elasticities of 0.65 and 0.87 respectively. (That the native response is larger than the aggregate is unexpected, but the standard errors are too large to conclude anything from this.) The impact of controlling for dynamics is intuitive. As Cadena and Kovak note, those MSAs that suffered larger downturns over 2006-10 had enjoyed larger upturns earlier in the decade. And therefore, the small native response in the first row of Table A11 may reflect a mixture between a (somewhat sluggish) response to a historic upturn and a contemporaneous downturn.

The fit in columns 1 and 2 of Panel C appears remarkably good, given the small sample of 94 MSAs - though this comes with the caveat of weak instruments. I report the associated first stage estimates in Panels D and E, for the employment change and initial employment rate respectively. In columns 1 and 2, each instrument has a strong positive effect (with a small standard error) on its corresponding endogenous variable - and no positive effect on the other. However, the Sanderson-Windmeijer (2016) F-statistics (which account for multiple endogenous variables) are small: between 5 and 6 in each case. Identification is especially weak in columns 3 and 4 (Mexicans and other migrants respectively), with F-statistics below 1; and furthermore, the instruments have counterintuitive effects in these two columns. This highlights the importance of pooling multiple decades of data, as I do in my own paper.

To summarize, once I account for dynamics, I estimate large native responses to local shocks - though weak instruments may be a problem. On the other hand, I do not have sufficient power to successfully identify the migrant elasticities (using the dynamic model) in this data.

Tables and figures

Table 1: First stage for average contributions

	Δ log emp	Lagged log emp rate	Δ log emp	Lagged log emp rate
	(1)	(2)	(3)	(4)
Current Bartik, b_{rt}	0.823***	-0.135*	0.839***	-0.134*
	(0.130)	(0.072)	(0.124)	(0.069)
Lagged Bartik, b_{rt-1}	0.102	0.369***	0.122*	0.371***
	(0.068)	(0.061)	(0.068)	(0.063)
Enclave shift-share, $\hat{\mu}^F_{rt}$			-0.233**	-0.022
			(0.113)	(0.122)
SW F-stat	51.65	37.67	52.83	38.06
Amenity×yr controls	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610

These are first stage estimates for IV specifications of Table 2. Columns 1-2 correspond to the Panel A specifications, and columns 3-4 to Panel B. The Sanderson-Windmeijer (2016) F-statistics account for multiple endogenous variables. All specifications control for year effects and the amenity variables (interacted with year effects) described in Section 3.5. Robust standard errors, clustered by state, are in parentheses. Observations are weighted by lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Average contributions to local population adjustment

	Population responses					Log emp rate responses		
	Aggregate response Δl_{rt}	Aggregate response Δl_{rt}	Foreign contrib $\hat{\lambda}^F_{rt}$	Residual contribution All: $\hat{\lambda}^I_{rt}$	Natives: $\hat{\lambda}^{I,N}_{rt}$	All indiv	Native	Migrant
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: No $\hat{\mu}^F_{rt}$ control								
Δ log emp	0.857***	0.748***	0.237**	0.527***	0.571***	0.252***	0.251***	0.167*
	(0.013)	(0.043)	(0.093)	(0.090)	(0.054)	(0.043)	(0.045)	(0.098)
Lagged log emp rate	0.246***	0.551***	0.313***	0.270*	0.258**	-0.551***	-0.560***	-0.609***
	(0.020)	(0.097)	(0.119)	(0.150)	(0.110)	(0.097)	(0.099)	(0.216)
Panel B: Controlling for $\hat{\mu}^F_{rt}$								
Δ log emp	0.858***	0.735***	0.130***	0.624***	0.629***	0.265***	0.266***	0.187**
	(0.014)	(0.040)	(0.039)	(0.049)	(0.042)	(0.040)	(0.042)	(0.094)
Lagged log emp rate	0.243***	0.530***	0.126*	0.441***	0.360***	-0.530***	-0.534***	-0.574***
	(0.019)	(0.096)	(0.065)	(0.123)	(0.096)	(0.096)	(0.098)	(0.221)
Enclave shift-share, $\hat{\mu}^F_{rt}$	0.133***	0.110*	0.952***	-0.870***	-0.517***	-0.110*	-0.134**	-0.176***
	(0.040)	(0.060)	(0.085)	(0.108)	(0.082)	(0.060)	(0.061)	(0.058)
Specification	OLS	IV	IV	IV	IV	IV	IV	IV
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,599

This table reports OLS and IV estimates of β_1 and β_2 in (27), across 722 CZs and five (decadal) time periods, for the aggregate change in log population, its (approximate) components, and changes in residualized log employment rates. Panel B controls additionally for the enclave shift-share, $\hat{\mu}^F_{rt}$. Robust standard errors, clustered by state, are in parentheses. Observations are weighted by lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Average IV contributions by education

	College graduates				Non-graduates			
	Aggregate response Δl_{rt}	Foreign contrib $\hat{\lambda}^F_{rt}$	Aggregate response Δl_{rt}	Foreign contrib $\hat{\lambda}^F_{rt}$	Aggregate response Δl_{rt}	Foreign contrib $\hat{\lambda}^F_{rt}$	Aggregate response Δl_{rt}	Foreign contrib $\hat{\lambda}^F_{rt}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ log emp	0.974***	0.585**	0.900***	0.191***	0.663***	0.217**	0.653***	0.128***
	(0.096)	(0.261)	(0.069)	(0.051)	(0.051)	(0.096)	(0.048)	(0.043)
Lagged log ER	2.819	3.864	2.128*	0.202	0.475***	0.322***	0.458***	0.157***
	(1.803)	(2.720)	(1.139)	(0.524)	(0.092)	(0.098)	(0.091)	(0.057)
Enclave shift-share, $\hat{\mu}^F_{rt}$			0.189*	0.999***			0.097	0.945***
			(0.108)	(0.078)			(0.070)	(0.094)
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610

This table reports education-specific IV estimates of (27), using education-specific population changes, employment changes, lagged employment rates, enclave shift-shares, and also education-specific Bartik instruments. See Appendix Table A3 for first stage estimates. Robust standard errors, clustered by state, are in parentheses. Observations are weighted by lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: First stage estimates for heterogeneous contributions

	Δ log emp	Δ log emp * $\hat{\lambda}^F_{rt}$	Lagged log ER	Lagged log ER * $\hat{\lambda}^F_{rt}$
	(1)	(2)	(3)	(4)
Current Bartik	0.993***	-0.007	-0.175***	0.004
	(0.123)	(0.006)	(0.065)	(0.003)
Current Bartik * $\hat{\mu}^F_{rt}$	-4.543	1.302***	1.440	-0.556***
	(3.110)	(0.173)	(1.025)	(0.074)
Lagged Bartik	0.095*	0.012***	0.337***	-0.004**
	(0.056)	(0.002)	(0.061)	(0.002)
Lagged Bartik * $\hat{\mu}^F_{rt}$	0.928	-0.245**	-0.434	0.446***
	(2.038)	(0.106)	(1.416)	(0.095)
$\hat{\mu}^F_{rt}$	-2.429	-0.216*	-0.691	-0.900***
	(2.012)	(0.111)	(1.815)	(0.167)
SW F-stat	72.13	25.74	30.61	15.37
Amenity×yr controls	Yes	Yes	Yes	Yes
Amenity×$\hat{\mu}^F_{rt}$ controls	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610

These first stage estimates correspond to the IV specifications in Table 5. The Sanderson-Windmeijer (2016) F-statistics account for multiple endogenous variables. All specifications control for year effects, the amenity variables of Section 3.5 interacted with year effects, and interactions between the amenity variables and the enclave shift-share. Robust standard errors, clustered by state, are in parentheses. Observations are weighted by lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Heterogeneity in contributions to population adjustment

	Population responses					ER responses		
	Aggregate response	Aggregate response	Foreign contrib	Residual contribution		All indiv	Native	Migrant
	Δl_{rt}	Δl_{rt}	$\hat{\lambda}^F_{rt}$	All: $\hat{\lambda}^I_{rt}$	Natives: $\hat{\lambda}^{I,N}_{rt}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ log emp	0.852***	0.791***	-0.006	0.809***	0.825***	0.209***	0.200***	0.193**
	(0.015)	(0.036)	(0.028)	(0.046)	(0.043)	(0.036)	(0.038)	(0.089)
Δ log emp * $\hat{\mu}^F_{rt}$	0.169	-0.689	4.908***	-5.326***	-8.410***	0.689	1.159	-1.551
	(0.247)	(0.804)	(1.180)	(1.127)	(1.325)	(0.804)	(0.773)	(1.502)
Lagged log ER	0.224***	0.560***	0.007	0.595***	0.579***	-0.560***	-0.577***	-0.577**
	(0.019)	(0.114)	(0.055)	(0.131)	(0.126)	(0.114)	(0.119)	(0.253)
Lagged log ER * $\hat{\mu}^F_{rt}$	1.842***	1.693	7.407***	-6.551***	-11.857***	-1.693	-1.168	-2.405
	(0.653)	(1.938)	(2.203)	(2.482)	(3.542)	(1.938)	(1.772)	(4.192)
$\hat{\mu}^F_{rt}$	0.138**	-0.039	1.016***	-1.038***	-0.593***	0.039	0.032	-0.093
	(0.068)	(0.143)	(0.123)	(0.191)	(0.174)	(0.143)	(0.138)	(0.257)
Specification	OLS	IV	IV	IV	IV	IV	IV	IV
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amenity×$\hat{\mu}^F_{rt}$ controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,599

This table reports OLS and IV estimates of equation (28), across 722 CZs and five (decadal) time periods. As in Table 2, I estimate this equation for the change in log population and its (approximate) components. All specifications control for year effects, the amenity variables described in Section in Section 3.5, interactions between the amenity variables and year effects, and interactions between the amenity variables and the enclave shift-share. Robust standard errors, clustered by state, are in parentheses. Observations are weighted by lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: First stage for semi-structural estimates

	Foreign contribution: $\hat{\lambda}^F_{rt}$			Δ log emp			Lagged log ER	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Current Bartik, b_{rt}	0.092***	0.078***	0.121***	0.839***	0.835***	0.866***	-0.134*	-0.156**
	(0.025)	(0.026)	(0.034)	(0.124)	(0.123)	(0.146)	(0.069)	(0.067)
Lagged Bartik, b_{rt-1}	0.063***	0.064***	0.160***	0.122*	0.122*	0.139*	0.371***	0.373***
	(0.019)	(0.019)	(0.028)	(0.068)	(0.068)	(0.079)	(0.063)	(0.062)
Current enclave, $\hat{\mu}^F_{rt}$	0.919***	1.229***	1.173***	-0.233**	-0.162	-0.201	-0.022	0.475***
	(0.084)	(0.119)	(0.105)	(0.113)	(0.171)	(0.174)	(0.122)	(0.175)
Lagged enclave, $\hat{\mu}^F_{rt-1}$		-0.399***	-0.377***		-0.091	-0.009		-0.640***
		(0.056)	(0.053)		(0.160)	(0.153)		(0.139)
SW F-test: 3 endog vars	93.68	50.69		84.09	97.40		56.93	66.49
SW F-test: 2 endog vars		117.72	134.14		53.90	38.88		
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year sample	60-10	60-10	70-10	60-10	60-10	70-10	60-10	60-10
Observations	3,610	3,610	2,888	3,610	3,610	2,888	3,610	3,610

This table reports first stage estimates corresponding to the semi-structural specifications in Table 7. I report Sanderson-Windmeijer F-statistics which account for multiple endogenous variables, both for those Table 7 specifications with two endogenous variables (i.e. $\hat{\lambda}^F_{rt}$ and the lagged employment rate) and those with three (the former two, plus the current change in log employment). Robust standard errors, clustered by state, are in parentheses. Observations are weighted by lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Semi-structural estimates of crowding out

	Basic estimates		Edu-specific variables		Robustness to dynamics			Native crowd-out	
	$\hat{\lambda}^I_{rt}$	$\hat{\lambda}^I_{rt}$	Grad $\hat{\lambda}^I_{rt}$	Non-grad $\hat{\lambda}^I_{rt}$	$\hat{\lambda}^I_{rt}$	$\hat{\lambda}^I_{rt}$	$\hat{\lambda}^I_{rt-1}$	$\hat{\lambda}^{I,N}_{rt}$	$\hat{\lambda}^{I,N}_{rt}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Foreign contrib: $\hat{\lambda}^F_{rt}$	-0.883***	-0.913***	-0.677***	-0.983***	-0.904***	-0.705***	-0.249	-0.543***	
	(0.048)	(0.065)	(0.093)	(0.078)	(0.085)	(0.094)	(0.233)	(0.079)	
Δ log emp	0.882***	0.743***	0.935***	0.658***	0.741***	0.619***	-0.0810	0.699***	0.737***
	(0.017)	(0.043)	(0.067)	(0.051)	(0.040)	(0.064)	(0.201)	(0.039)	(0.044)
Lagged log ER	0.251***	0.556***	1.800*	0.482***	0.555***			0.428***	0.524***
	(0.021)	(0.105)	(0.922)	(0.100)	(0.109)			(0.094)	(0.103)
Lagged Bartik, b_{rt-1}						0.209***	0.921***		
						(0.031)	(0.106)		
Lagged enclave, $\hat{\mu}^F_{rt-1}$					-0.012	-0.299***	-0.990***		
					(0.072)	(0.073)	(0.173)		
Total migrant contrib									-0.818***
									(0.104)
Specification	OLS	IV	IV	IV	IV	IV	IV	IV	IV
Instruments	-	$\hat{\mu}^F_{rt}$, b_{rt}, b_{rt-1}	$\hat{\mu}^F_{rt}$, b_{rt}, b_{rt-1}	$\hat{\mu}^F_{rt}$, b_{rt}, b_{rt-1}	$\hat{\mu}^F_{rt}$, b_{rt}, b_{rt-1}	$\hat{\mu}^F_{rt}$, b_{rt}	$\hat{\mu}^F_{rt}$, b_{rt}	$\hat{\mu}^F_{rt}$, b_{rt}, b_{rt-1}	$\hat{\mu}^F_{rt}$, b_{rt}, b_{rt-1}
p-value: $\delta_1 = -\delta_2$	0.974	0.013	0.001	0.000	0.075	0.391	0.270	0.087	0.421
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year sample	60-10	60-10	60-10	60-10	60-10	60-10	70-10	60-10	60-10
Observations	3,610	3,610	3,610	3,610	3,610	3,610	2,888	3,610	3,610

This table reports variants of the semi-structural equation (29). There are (up to) three endogenous variables: the foreign contribution to population growth, $\hat{\lambda}^F_{rt}$, the log employment change, and the lagged log employment rate. The corresponding instruments are the enclave shift-share $\hat{\mu}^F_{rt}$ and the current and lagged Bartiks. Columns 3-4 use education-specific variables, as described in the text. Column 7 replaces the dependent variable with its lag, so it omits the initial decade. Columns 8-9 replaces the dependent with the native contribution alone, and column 9 replaces the foreign contribution with the total migrant contribution (i.e. including old migrants). Robust standard errors, clustered by state, are in parentheses. Observations are weighted by lagged local population share. *** p<0.01, ** p<0.05, * p<0.1. P-values test the hypothesis that $\delta_1 = -\delta_2$, i.e. that the coefficients in the first two rows sum to zero.

Table 8: Evolution of enclave shift-share, $\hat{\mu}^F_{rt}$

	(1)	(2)	(3)	(4)
$\hat{\mu}^F_{rt-1}$	1.007***	1.000***	0.543***	0.531***
	(0.039)	(0.040)	(0.051)	(0.056)
Lagged foreign contrib: $\hat{\lambda}^F_{rt-1}$			0.469***	0.472***
			(0.072)	(0.075)
Lagged internal contrib: $\hat{\lambda}^I_{rt-1}$				-0.009
				(0.007)
Amenity×yr controls	Yes	Yes	Yes	Yes
Year sample	60-10	70-10	70-10	70-10
Observations	3,610	2,888	2,888	2,888

This table estimates OLS models for the enclave shift-share, $\hat{\mu}^F_{rt}$. All specifications control for year effects and the amenity variables (interacted with year effects) described in Section 3.5. Robust standard errors, clustered by state, are in parentheses. Observations are weighted by lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Autoregressive models for composite employment shock, x_{rt}

	(1)	(2)	(3)	(4)	(5)	(6)
x_{rt-1}	0.635***	0.561***	0.661***	0.852***	0.353***	0.579***
	(0.025)	(0.054)	(0.033)	(0.068)	(0.018)	(0.155)
x_{rt-2}					0.400***	0.307***
					(0.016)	(0.117)
Specification	OLS	IV	OLS	IV	OLS	IV
Instruments	-	b_{rt-1}	-	b_{rt-1}	-	b_{rt-1}, b_{rt-2}
F-tests	-	37.79		15.91	-	30.77, 53.83
Implied sum of autocorrelations	1.74	1.28	1.95	5.77	3.99	9.95
Implied foreign contribution (%)	20.0	17.6	21.1	40.7	31.6	62.3
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes
Year sample	70-10	70-10	80-10	80-10	80-10	80-10
Observations	2,888	2,888	2,166	2,166	2,166	2,166

This table presents OLS and IV estimates of AR(1) and AR(2) processes for the composite employment shock, x_{rt}, whose values I impute using (36). Column 6 reports Sanderson-Windmeijer F-statistics which account for multiple endogenous variables. The sum of autocorrelations, $\sum_{i>0} \frac{Cov(x_{rt}, x_{rt-i})}{Var(x_{rt})}$, is computed using the coefficient estimates, as described in Appendix B.6. The implied foreign contribution $\mathbb{E}\left[\frac{Cov(\lambda^F_{rt}, x_{rt})}{Cov(\Delta l_{rt}, x_{rt})}\right]$ is computed according to equation (35), assuming the foreign share of gross flows $\frac{\bar{\mu}^F}{\mu^I} = 0.11$, $\theta = 0.469$, and $\gamma^F = \gamma^I$, i.e. equal foreign and internal elasticities. All specifications control for year effects and the amenity variables (interacted with year effects) described in Section 3.5. Robust standard errors, clustered by state, are in parentheses. Observations are weighted by lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A1: Average contributions to local adjustment: OLS, RF

	Population responses				Emp rate responses		
	Aggregate response	Foreign contrib	Residual contribution		All indiv	Native	Migrant
	Δl_{rt}	$\hat{\lambda}^F_{rt}$	All: $\hat{\lambda}^I_{rt}$	Natives: $\hat{\lambda}^{I,N}_{rt}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
Δ log emp	0.857***	0.050***	0.838***	0.781***	0.143***	0.139***	0.166***
	(0.013)	(0.017)	(0.024)	(0.019)	(0.013)	(0.014)	(0.023)
Lagged log ER	0.246***	0.089*	0.172***	0.131***	-0.246***	-0.238***	-0.264***
	(0.020)	(0.052)	(0.053)	(0.040)	(0.020)	(0.021)	(0.039)
Panel B: Reduced form							
Current Bartik	0.541***	0.152***	0.397**	0.435***	0.282***	0.282***	0.218**
	(0.116)	(0.055)	(0.154)	(0.120)	(0.038)	(0.040)	(0.093)
Lagged Bartik	0.280***	0.140***	0.154*	0.154**	-0.178***	-0.181***	-0.205***
	(0.062)	(0.033)	(0.079)	(0.066)	(0.025)	(0.026)	(0.066)
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,599

This table reports OLS and reduced form estimates of the average contributions to local adjustment, corresponding to the IV estimates in Table 2 of the main text. See notes under Table 2 for further details. Robust standard errors, clustered by state, are in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Heterogeneity in contributions to local adjustment: OLS, RF

	Population responses				Emp rate responses		
	Aggregate response	Foreign contrib	Residual contribution		All indiv	Native	Migrant
	Δl_{rt}	$\hat{\lambda}^F_{rt}$	All: $\hat{\lambda}^I_{rt}$	Natives: $\hat{\lambda}^{I,N}_{rt}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
Δ log emp	0.852***	0.004	0.859***	0.852***	0.148***	0.145***	0.195***
	(0.015)	(0.012)	(0.015)	(0.018)	(0.015)	(0.015)	(0.027)
Δ log emp * $\hat{\mu}^F_{rt}$	0.169	1.930***	-1.030***	-2.877***	-0.169	-0.184	-1.128**
	(0.247)	(0.376)	(0.379)	(0.515)	(0.247)	(0.258)	(0.527)
Lagged log ER	0.224***	0.021	0.211***	0.211***	-0.224***	-0.224***	-0.194***
	(0.019)	(0.012)	(0.020)	(0.021)	(0.019)	(0.019)	(0.040)
Lagged log ER * $\hat{\mu}^F_{rt}$	1.842***	1.757***	0.501	-2.384***	-1.842***	-1.328**	-4.274***
	(0.653)	(0.647)	(0.535)	(0.377)	(0.653)	(0.621)	(1.145)
$\hat{\mu}^F_{rt}$	0.138**	1.108***	-0.969***	-0.569***	-0.138**	-0.182***	-0.165**
	(0.068)	(0.056)	(0.074)	(0.063)	(0.068)	(0.066)	(0.074)
Panel B: Reduced form							
Current Bartik	0.700***	-0.007	0.706***	0.722***	0.293***	0.287***	0.291**
	(0.113)	(0.023)	(0.112)	(0.104)	(0.043)	(0.045)	(0.110)
Current Bartik * $\hat{\mu}^F_{rt}$	-4.627**	2.310***	-6.112**	-7.275***	0.084	0.416	-2.384
	(2.104)	(0.605)	(2.384)	(1.969)	(1.177)	(1.203)	(1.563)
Lagged Bartik	0.248***	0.028***	0.243***	0.225***	-0.153***	-0.156***	-0.181**
	(0.042)	(0.010)	(0.044)	(0.041)	(0.027)	(0.026)	(0.070)
Lagged Bartik * $\hat{\mu}^F_{rt}$	1.415	2.092***	-1.124	-2.712*	-0.487	-0.368	-0.285
	(1.636)	(0.313)	(1.520)	(1.363)	(1.046)	(0.951)	(1.743)
$\hat{\mu}^F_{rt}$	0.041	1.044***	-0.999***	-0.594**	-0.271***	-0.284***	-0.358***
	(0.366)	(0.087)	(0.344)	(0.263)	(0.075)	(0.077)	(0.102)
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amenity×$\hat{\mu}^F_{rt}$ controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,599

This table reports OLS and reduced form estimates of the contributions to local adjustment, allowing for heterogeneity by the enclave shift-share $\hat{\mu}^F_{rt}$. These estimates correspond to the IV estimates in Table 5 of the main text. See notes under Table 5 for further details. Robust standard errors, clustered by state, are in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: First stage for education-specific average contributions

	College graduates				Non-graduates			
	Δ log emp	Lagged log ER	Δ log emp	Lagged log ER	Δ log emp	Lagged log ER	Δ log emp	Lagged log ER
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Current Bartik	0.760***	-0.028	0.829***	-0.006	0.795***	-0.148*	0.809***	-0.147*
	(0.224)	(0.029)	(0.193)	(0.028)	(0.105)	(0.081)	(0.100)	(0.078)
Lagged Bartik	0.196**	0.019	0.247***	0.035**	0.014	0.443***	0.038	0.445***
	(0.086)	(0.015)	(0.087)	(0.016)	(0.064)	(0.070)	(0.062)	(0.071)
$\hat{\mu}^F_{rt}$			-0.349*	-0.109***			-0.295**	-0.016
			(0.193)	(0.026)			(0.116)	(0.139)
SW F-stat	5.39	2.51	9.35	3.86	100.39	69.45	113.42	70.61
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amenity×$\hat{\mu}^F_{rt}$ controls	No	No	No	No	No	No	No	No
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610

This table presents first stage estimates corresponding to the education-specific IV specifications in Table 3. I construct employment changes, lagged employment rates, enclaved shift-shares and Bartik instruments using education-specific data, as I describe in Section 4.4. The Sanderson-Windmeijer (2016) F-statistics account for multiple endogenous variables. See notes under Table 3 for further details. Robust standard errors, clustered by state, are in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: First stage for education-specific semi-structural estimates

	College graduates			Non-graduates		
	Foreign contrib $\hat{\lambda}^F_{rt}$	Δ log emp	Lagged log ER	Foreign contrib $\hat{\lambda}^F_{rt}$	Δ log emp	Lagged log ER
	(1)	(2)	(3)	(4)	(5)	(6)
Current Bartik	0.157***	0.829***	-0.006	0.080***	0.809***	-0.147*
	(0.026)	(0.193)	(0.028)	(0.026)	(0.100)	(0.078)
Lagged Bartik	0.054**	0.247***	0.035**	0.075***	0.038	0.445***
	(0.022)	(0.087)	(0.016)	(0.021)	(0.062)	(0.071)
$\hat{\mu}^F_{rt}$	0.910***	-0.349*	-0.109***	0.905***	-0.295**	-0.016
	(0.099)	(0.193)	(0.026)	(0.088)	(0.116)	(0.139)
SW F-test	6.19	4.91	4.25	85.08	120.54	71.32
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610	3,610	3,610

This table presents first stage estimates corresponding to the education-specific semi-structural IV specifications in columns 6-7 of Table 7. I construct employment changes, lagged employment rates, enclaved shift-shares and Bartik instruments using education-specific data, as I describe in Section 4.4. The Sanderson-Windmeijer (2016) F-statistics account for multiple endogenous variables. See notes under Table 7 for further details. Robust standard errors, clustered by state, are in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Robustness of IV contributions: Specification choices

	Aggregate response	Foreign contribution	Residual contribution		Aggregate response	Foreign contribution	Residual contribution	
	Δl_{rt}	$\hat{\lambda}^F_{rt}$	All: $\hat{\lambda}^I_{rt}$	Natives: $\hat{\lambda}^{I,N}_{rt}$	Δl_{rt}	$\hat{\lambda}^F_{rt}$	All: $\hat{\lambda}^I_{rt}$	Natives: $\hat{\lambda}^{I,N}_{rt}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Original specification								
Δ log emp	0.748***	0.237**	0.527***	0.571***	0.791***	-0.006	0.809***	0.825***
	(0.043)	(0.093)	(0.090)	(0.054)	(0.036)	(0.028)	(0.046)	(0.043)
Δ log emp * $\hat{\mu}^F_{rt}$					-0.689	4.908***	-5.326***	-8.410***
					(0.804)	(1.180)	(1.127)	(1.325)
Lagged log ER	0.551***	0.313***	0.270*	0.258**	0.560***	0.007	0.595***	0.579***
	(0.097)	(0.119)	(0.150)	(0.110)	(0.114)	(0.055)	(0.131)	(0.126)
Lagged log ER * $\hat{\mu}^F_{rt}$					1.693	7.407***	-6.551***	-11.857***
					(1.938)	(2.203)	(2.482)	(3.542)
$\hat{\mu}^F_{rt}$					-0.039	1.016***	-1.038***	-0.593***
					(0.143)	(0.123)	(0.191)	(0.174)
Panel B: Controlling for CZ fixed effects								
Δ log emp	0.653***	-0.054**	0.727***	0.650***	0.719***	-0.014	0.728***	0.723***
	(0.058)	(0.021)	(0.059)	(0.054)	(0.049)	(0.029)	(0.046)	(0.046)
Δ log emp * $\hat{\mu}^F_{rt}$					-1.473*	2.882***	-4.013***	-7.052***
					(0.806)	(0.309)	(0.814)	(0.736)
Lagged log ER	1.178***	0.185	1.033***	0.852***	0.997***	0.356**	0.634**	0.410
	(0.329)	(0.229)	(0.217)	(0.245)	(0.194)	(0.150)	(0.279)	(0.363)
Lagged log ER * $\hat{\mu}^F_{rt}$					-1.039	7.299***	-9.201***	-15.586***
					(2.092)	(2.133)	(1.920)	(2.849)
$\hat{\mu}^F_{rt}$					0.438**	0.602***	-0.142	0.308
					(0.215)	(0.172)	(0.250)	(0.343)
Panel C: Excluding lagged employment rate								
Δ log emp	0.870***	0.306***	0.587***	0.628***	0.855***	0.000	0.872***	0.883***
	(0.028)	(0.076)	(0.089)	(0.057)	(0.032)	(0.033)	(0.034)	(0.030)
Δ log emp * $\hat{\mu}^F_{rt}$					-0.468	3.175***	-3.127***	-4.982***
					(0.396)	(0.787)	(0.643)	(0.672)
$\hat{\mu}^F_{rt}$					0.296***	1.271***	-0.965***	-0.709***
					(0.112)	(0.101)	(0.136)	(0.106)
Panel D: Raw employment variables								
Δ log emp	0.630***	0.185**	0.457***	0.499***	0.680***	0.013	0.672***	0.674***
	(0.039)	(0.085)	(0.097)	(0.058)	(0.034)	(0.032)	(0.037)	(0.038)
Δ log emp * $\hat{\mu}^F_{rt}$					-0.236	4.257***	-3.977***	-6.442***
					(0.752)	(1.403)	(1.306)	(1.405)
Lagged log ER	0.388***	0.217***	0.193*	0.185**	0.397***	-0.024	0.449***	0.454***
	(0.076)	(0.073)	(0.115)	(0.086)	(0.091)	(0.043)	(0.109)	(0.105)
Lagged log ER * $\hat{\mu}^F_{rt}$					2.328	6.291***	-4.309***	-8.509***
					(2.012)	(1.718)	(1.526)	(1.827)
$\hat{\mu}^F_{rt}$					0.933	3.033***	-2.310***	-3.272***
					(0.776)	(0.641)	(0.647)	(0.745)
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amenity×$\hat{\mu}^F_{rt}$ controls	No	No	No	No	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610

This table replicates the IV estimates from columns 2-5 (Panel A) of Table 2 and columns 2-5 of Table 5, subject to various changes of specification. Employment variables are composition-adjusted in all specifications except in Panel D. Robust standard errors, clustered by state, are in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1. See Appendix F.1 for discussion of the estimates.

Table A6: Robustness of IV contributions: Amenity controls

	Aggregate response Δl_{rt}	Foreign contribution $\hat{\lambda}_{rt}^{F}$	Residual contribution		Aggregate response Δl_{rt}	Foreign contribution $\hat{\lambda}_{rt}^{F}$	Residual contribution	
			All: $\hat{\lambda}_{rt}^{I}$	Natives: $\hat{\lambda}_{rt}^{I,N}$			All: $\hat{\lambda}_{rt}^{I}$	Natives: $\hat{\lambda}_{rt}^{I,N}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Year effects only								
Δ log emp	0.851***	0.399*	0.468*	0.581***	0.799***	0.068	0.741***	0.813***
	(0.052)	(0.229)	(0.240)	(0.092)	(0.057)	(0.114)	(0.158)	(0.127)
Δ log emp * $\hat{\mu}_{rt}^{F}$					-0.616	7.248	-8.208	-11.165
					(0.759)	(8.017)	(9.829)	(9.260)
Lagged log ER	0.394***	0.841**	-0.426	-0.048	0.234***	0.380	-0.138	0.007
	(0.086)	(0.428)	(0.401)	(0.185)	(0.070)	(0.362)	(0.452)	(0.390)
Lagged log ER * $\hat{\mu}_{rt}^{F}$					-0.027	11.284	-13.054	-16.914
					(1.237)	(13.308)	(15.582)	(15.559)
$\hat{\mu}_{rt}^{F}$					0.227***	0.771***	-0.510**	-0.190
					(0.052)	(0.211)	(0.254)	(0.274)
*Panel B: ... + amenity * year interactions*								
Δ log emp	0.748***	0.237**	0.527***	0.571***	0.752***	0.027	0.738***	0.782***
	(0.043)	(0.093)	(0.090)	(0.054)	(0.039)	(0.054)	(0.067)	(0.068)
Δ log emp * $\hat{\mu}_{rt}^{F}$					-0.107	8.972	-9.258*	-12.188**
					(2.092)	(5.796)	(4.814)	(5.079)
Lagged log ER	0.551***	0.313***	0.270*	0.258**	0.487***	-0.172	0.725***	0.725***
	(0.097)	(0.119)	(0.150)	(0.110)	(0.110)	(0.277)	(0.266)	(0.256)
Lagged log ER * $\hat{\mu}_{rt}^{F}$					2.174	16.061	-15.370*	-19.784**
					(4.261)	(10.327)	(8.908)	(10.076)
$\hat{\mu}_{rt}^{F}$					0.054	0.767***	-0.708***	-0.316
					(0.077)	(0.195)	(0.244)	(0.240)
*Panel C: ... + amenity * $\hat{\mu}_{rt}^{F}$ interactions*								
Δ log emp	0.764***	0.195***	0.592***	0.597***	0.791***	-0.006	0.809***	0.825***
	(0.043)	(0.050)	(0.057)	(0.051)	(0.036)	(0.028)	(0.046)	(0.043)
Δ log emp * $\hat{\mu}_{rt}^{F}$					-0.689	4.908***	-5.326***	-8.410***
					(0.804)	(1.180)	(1.127)	(1.325)
Lagged log ER	0.585***	0.286***	0.329**	0.322***	0.560***	0.007	0.595***	0.579***
	(0.107)	(0.085)	(0.129)	(0.108)	(0.114)	(0.055)	(0.131)	(0.126)
Lagged log ER * $\hat{\mu}_{rt}^{F}$					1.693	7.407***	-6.551***	-11.857***
					(1.938)	(2.203)	(2.482)	(3.542)
$\hat{\mu}_{rt}^{F}$					-0.039	1.016***	-1.038***	-0.593***
					(0.143)	(0.123)	(0.191)	(0.174)
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610

This table replicates the IV estimates from columns 2-5 (Panel A) of Table 2 and columns 2-5 of Table 5, subject to various combinations of right hand side controls. Robust standard errors, clustered by state, are in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1. See Appendix F.2 for discussion of the estimates.

Table A7: Robustness of IV contributions: Sample and weights

	Aggregate response	Foreign contribution	Residual contribution		Aggregate response	Foreign contribution	Residual contribution	
	Δl_{rt}	$\hat{\lambda}^F_{rt}$	All: $\hat{\lambda}^I_{rt}$	Natives: $\hat{\lambda}^{I,N}_{rt}$	Δl_{rt}	$\hat{\lambda}^F_{rt}$	All: $\hat{\lambda}^I_{rt}$	Natives: $\hat{\lambda}^{I,N}_{rt}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Weighted + Excluding observations with $\hat{\mu}^F_{rt} > 0.1$ (N = 3,544; 88% of pop)								
Δ log emp	0.761***	0.265***	0.510***	0.575***	0.834***	-0.044	0.898***	0.913***
	(0.043)	(0.084)	(0.085)	(0.058)	(0.053)	(0.028)	(0.070)	(0.072)
Δ log emp * $\hat{\mu}^F_{rt}$					-3.077	8.488**	-12.478*	-15.216**
					(3.623)	(3.714)	(6.995)	(7.545)
Lagged log ER	0.501***	0.142	0.406***	0.313***	0.540***	-0.036	0.608***	0.576***
	(0.093)	(0.116)	(0.144)	(0.113)	(0.105)	(0.062)	(0.135)	(0.139)
Lagged log ER * $\hat{\mu}^F_{rt}$					-0.230	6.510*	-7.763	-11.487
					(3.367)	(3.712)	(7.486)	(7.667)
$\hat{\mu}^F_{rt}$					0.037	0.893***	-0.750	-0.273
					(0.244)	(0.265)	(0.516)	(0.507)
Panel B: Unweighted (N = 3,610; 100% of pop)								
Δ log emp	0.759***	0.098***	0.677***	0.686***	0.780***	0.016**	0.773***	0.798***
	(0.038)	(0.017)	(0.042)	(0.040)	(0.040)	(0.007)	(0.042)	(0.042)
Δ log emp * $\hat{\mu}^F_{rt}$					1.607*	1.968***	0.078	-4.457***
					(0.854)	(0.475)	(1.097)	(1.132)
Lagged log ER	0.444***	0.129***	0.333***	0.315***	0.455***	0.029**	0.443***	0.444***
	(0.067)	(0.031)	(0.059)	(0.060)	(0.080)	(0.013)	(0.082)	(0.074)
Lagged log ER * $\hat{\mu}^F_{rt}$					4.565***	3.592***	1.091	-7.071***
					(1.708)	(0.783)	(2.057)	(1.908)
$\hat{\mu}^F_{rt}$					-0.352*	0.930***	-1.288***	-0.670***
					(0.182)	(0.045)	(0.184)	(0.152)
Panel C: Unweighted + Excluding CZs with 1960 population of 16-64s < 25,000 (N = 2,425; 98% of pop)								
Δ log emp	0.765***	0.102***	0.679***	0.690***	0.791***	0.015***	0.785***	0.801***
	(0.038)	(0.019)	(0.041)	(0.040)	(0.042)	(0.006)	(0.043)	(0.042)
Δ log emp * $\hat{\mu}^F_{rt}$					-0.001	1.989***	-1.570	-5.041***
					(0.752)	(0.501)	(1.010)	(1.209)
Lagged log ER	0.434***	0.139***	0.315***	0.303***	0.454***	0.034***	0.437***	0.425***
	(0.067)	(0.034)	(0.066)	(0.066)	(0.077)	(0.013)	(0.080)	(0.076)
Lagged log ER * $\hat{\mu}^F_{rt}$					1.699	4.171***	-2.456	-8.771***
					(1.496)	(0.618)	(1.616)	(1.478)
$\hat{\mu}^F_{rt}$					-0.038	0.897***	-0.918***	-0.441***
					(0.125)	(0.049)	(0.121)	(0.149)
Panel D: Unweighted + Excluding CZs with 1960 population of 16-64s < 50,000 (N = 1,675; 93% of pop)								
Δ log emp	0.749***	0.105***	0.661***	0.669***	0.769***	0.011	0.767***	0.785***
	(0.034)	(0.023)	(0.038)	(0.035)	(0.039)	(0.008)	(0.039)	(0.039)
Δ log emp * $\hat{\mu}^F_{rt}$					-0.335	2.257***	-2.143*	-5.521***
					(0.802)	(0.598)	(1.094)	(1.376)
Lagged log ER	0.427***	0.143***	0.303***	0.308***	0.442***	0.033**	0.425***	0.421***
	(0.052)	(0.041)	(0.051)	(0.048)	(0.054)	(0.014)	(0.058)	(0.057)
Lagged log ER * $\hat{\mu}^F_{rt}$					0.875	5.051***	-4.108**	-10.391***
					(1.999)	(0.866)	(1.796)	(1.791)
$\hat{\mu}^F_{rt}$					0.067	0.878***	-0.792***	-0.331**
					(0.097)	(0.068)	(0.095)	(0.131)
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amenity×$\hat{\mu}^F_{rt}$ controls	No	No	No	No	Yes	Yes	Yes	Yes

This table replicates the IV estimates from columns 2-5 (Panel A) of Table 2 and columns 2-5 of Table 5, subject to various weighting choices (i.e. with or without lagged local population share weights) and sample choices. Robust standard errors, clustered by state, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. See Appendix F.3 for discussion of the estimates.

Table A8: Contribution of old migrants to local population adjustment

	Overall: $\hat{\lambda}_{rt}^{I,OM}$ (1)	Within-cohort: $\hat{\lambda}_{rt}^{I,OM,cohort}$ (2)	Overall: $\hat{\lambda}_{rt}^{I,OM}$ (3)	Within-cohort: $\hat{\lambda}_{rt}^{I,OM,cohort}$ (4)
Δ log emp	-0.039	0.002	0.002	0.032*
	(0.050)	(0.031)	(0.026)	(0.018)
Lagged log ER	0.011	-0.008	0.082	0.045
	(0.061)	(0.038)	(0.054)	(0.031)
Enclave shift-share, $\hat{\mu}_{rt}^{F}$			-0.363***	-0.273***
			(0.061)	(0.038)
Amenity×yr controls	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610

This table re-estimates the IV regressions in Panels A and B of Table 2, but replacing the dependent variable with the overall contribution of old migrants (i.e. those living in the US since period $t-1$) and the within-cohort contribution, as defind by equations (A42) and (A43) in Appendix F.4. Otherwise, the specifications are identical to Table 2. Robust standard errors, clustered by state, are in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Average IV foreign contributions by country/region of origin

	Total foreign contribution (1)	Mexico (2)	Other Latin America (3)	Europe and former USSR (4)	Asia (5)	Other (6)
Δ log emp	0.237**	-0.010	0.127***	0.042***	0.045**	0.041***
	(0.093)	(0.020)	(0.047)	(0.012)	(0.022)	(0.013)
Lagged log ER	0.313***	0.089***	0.094	0.033**	0.105**	0.009
	(0.119)	(0.034)	(0.065)	(0.014)	(0.042)	(0.014)
% foreign inflows	100	26.9	23.8	14.6	26.6	8.1
Amenity×yr controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610	3,610	3,610

This table breaks down the foreign contribution in column 3 (Panel A) of Table 2 into approximate contributions from origin country groups. For each origin group o, I replace the dependent variable of equation (27) with $\hat{\lambda}_{rt}^{Fo} \equiv \log\left(\frac{L_{rt-1}+L_{rt}^{Fo}}{L_{rt-1}}\right)$. Otherwise, the specifications are identical to Table 2. Robust standard errors, clustered by state, are in parentheses. Each observation is weighted by the lagged local population share. *** p<0.01, ** p<0.05, * p<0.1. See Appendix F.5 for discussion of the estimates.

Table A10: Robustness of IV semi-structural crowding out estimates

	1960s (1)	1970s (2)	1980s (3)	1990s (4)	2000s (5)	All years (6)
Panel A: Weighted estimates						
Year effects	0.273	-0.726	-0.041	-0.943***	-0.538**	-0.526**
	(0.944)	(0.635)	(0.250)	(0.225)	(0.252)	(0.246)
+ Δ log emp (instrumented)	-0.370	-1.090***	-0.663***	-1.068	-0.686***	-0.775***
	(0.231)	(0.154)	(0.080)	(0.724)	(0.216)	(0.060)
+ Lagged log ER (instrumented)	-0.401*	-1.081***	-0.698***	-0.601***	-0.669***	-0.746***
	(0.238)	(0.126)	(0.129)	(0.118)	(0.186)	(0.073)
+ Climate controls	-0.651***	-1.567*	-1.624	0.237	-0.884***	-0.948***
	(0.223)	(0.800)	(15.570)	(2.153)	(0.136)	(0.065)
+ Coastline dummy	-0.654***	-1.560*	-1.125	1.968	-0.788***	-0.897***
	(0.245)	(0.810)	(6.460)	(24.446)	(0.171)	(0.075)
+ Log pop density 1900	-0.578**	-1.090***	-0.818***	-3.113	-0.734***	-0.841***
	(0.282)	(0.114)	(0.311)	(20.892)	(0.188)	(0.068)
+ Log distance to closest CZ	-0.631**	-1.158***	-0.689***	23.645	-0.807***	-0.893***
	(0.261)	(0.128)	(0.244)	(1886.724)	(0.199)	(0.068)
+ Amenity×yr effects	-0.631**	-1.158***	-0.689***	23.645	-0.807***	-0.913***
	(0.261)	(0.128)	(0.244)	(1886.724)	(0.199)	(0.065)
Panel B: Unweighted estimates						
Year effects	2.794**	0.912	1.193***	-0.030	0.395**	0.775***
	(1.173)	(0.564)	(0.307)	(0.214)	(0.194)	(0.270)
+ Δ log emp (instrumented)	0.431	-0.286	0.314	-0.177	1.353*	-0.329***
	(0.344)	(0.384)	(0.351)	(0.268)	(0.822)	(0.104)
+ Lagged log ER (instrumented)	0.263	-1.127***	0.517	0.553	1.132*	-0.183
	(0.349)	(0.311)	(1.033)	(0.920)	(0.675)	(0.168)
+ Climate controls	-0.215	-0.704***	-0.535*	-1.122***	-0.818**	-0.753***
	(0.366)	(0.177)	(0.301)	(0.147)	(0.343)	(0.138)
+ Coastline dummy	-0.198	-0.645***	-0.534*	-1.048***	-0.796**	-0.712***
	(0.394)	(0.180)	(0.276)	(0.144)	(0.335)	(0.147)
+ Log pop density 1900	-0.226	-0.632***	-0.570**	-1.075***	-0.765**	-0.714***
	(0.397)	(0.180)	(0.265)	(0.166)	(0.305)	(0.146)
+ Log distance to closest CZ	-0.364	-0.761***	-0.549**	-1.151***	-0.870***	-0.791***
	(0.358)	(0.187)	(0.236)	(0.167)	(0.287)	(0.132)
+ Amenity×yr effects	-0.364	-0.761***	-0.549**	-1.151***	-0.870***	-0.884***
	(0.358)	(0.187)	(0.236)	(0.167)	(0.287)	(0.097)
Observations	722	722	722	722	722	3,610

This table tests the robustness of my IV crowding out estimate δ_1 (in column 2 of Table 7) to the choice of controls and decadal sample. The various columns report estimates of δ_1 separately for each decade, and for all decades together. Moving down the rows of the table, I show how my δ_1 estimate changes as progressively more controls are included. All specifications include the foreign contribution $\hat{\lambda}_{rt}^F$ (instrumented with the enclave shift-share, $\hat{\mu}_{rt}^F$) and year effects. The second row controls additionally for the (endogenous) employment change (together with its current Bartik instrument, b_{rt}); the third row includes the (endogenous) lagged employment rate (with its lagged Bartik instrument, b_{rt-1}); and the various amenities are then progressively added - until the final row, which includes the full set of controls I use in Table 7. Panel B repeats the exercise without the lagged local population share weights. Robust standard errors, clustered by state, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. See Appendix G.2 for discussion of the estimates.

Table A11: Reconciliation with IV population responses from Cadena and Kovak (2016)

	All	Natives	Mexican migrants	Other migrants
	(1)	(2)	(3)	(4)
Panel A: Cadena and Kovak's Panel A, Table 4				
W/i-industry shock: group-specific	0.223	0.007	0.992**	-0.675**
	(0.166)	(0.090)	(0.468)	(0.278)
Panel B: As above, but replace $IndShock_{gr}$ with Δn_{gr}				
Δ log emp: group-specific	0.301*	0.013	0.771***	1.413***
	(0.170)	(0.159)	(0.104)	(0.356)
Panel C: Control for dynamics				
Δ log emp: group-specific	0.654***	0.871**	0.380	1.470***
	(0.199)	(0.441)	(0.413)	(0.552)
Log ER in 2006: group-specific	0.680**	0.745***	-2.429	-0.519
	(0.305)	(0.284)	(2.651)	(2.753)
Panel D: First stage for Δ log emp in Panel C specification				
Bartik 2006-10	2.928***	1.789**	7.805***	-3.342*
	(0.763)	(0.734)	(1.661)	(1.814)
Bartik 2000-06	0.223	0.558	-2.013*	1.387
	(0.575)	(0.548)	(1.208)	(1.337)
Panel E: First stage for log ER in 2006 in Panel C specification				
Bartik 2006-10	-2.777***	-3.936***	-1.075**	-0.643
	(0.625)	(1.352)	(0.501)	(0.812)
Bartik 2000-06	1.402***	1.507***	0.029	0.506
	(0.485)	(0.513)	(0.303)	(0.697)
SW F-stats for Panel C				
Δ log emp	5.30	5.54	1.05	0.62
Log ER in 2006	4.94	5.42	0.97	0.32
Amenity controls	No	No	No	No
Observations	94	94	94	94

This table offers a reconciliation with Panel A of Cadena and Kovak's (2016) Table 4. The reported coefficients are estimates of ω_1 in various specifications of equation (A44). All estimates correspond to men with no college education. Throughout, I use Cadena and Kovak's sample of 94 MSAs over the period 2006-10. Panel A reproduces Cadena and Kovak's own estimates of ω_{1g}, instrumenting the within-industry shock with a Bartik shift-share. Panel B replaces the within-industry shock with the overall change in employment, but retaining the same instrument. Panel C controls additionally for the lagged employment rate in 2006, which I instrument with a lagged Bartik shift-share (predicting employment changes in the period 2000-6). Panels D and E report the first stage estimates (for the two endogenous variables) for the dynamic specification (i.e. with the lagged employment rate). The associated Sanderson-Windmeijer (2016) F-statistics account for multiple endogenous variables. In line with Cadena and Kovak, all specifications control for the Mexican population share in 2000 and indicators for MSAs in states that enacted anti-migrant employment legislation. *** p<0.01, ** p<0.05, * p<0.1. See Appendix H for discussion of the estimates.

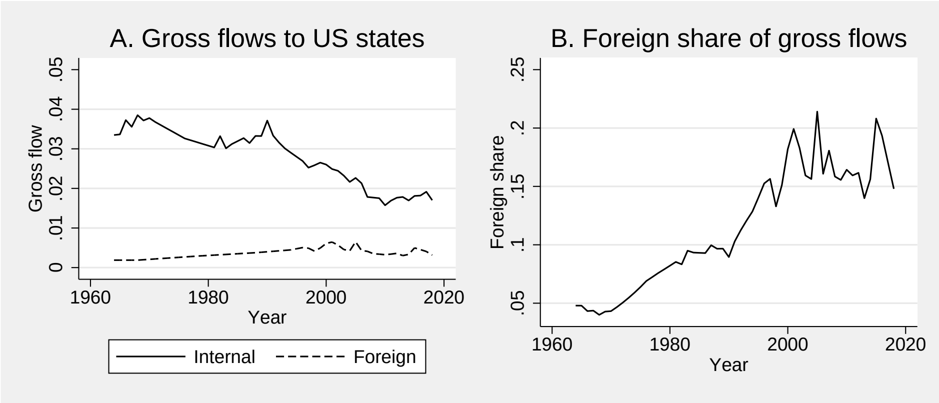
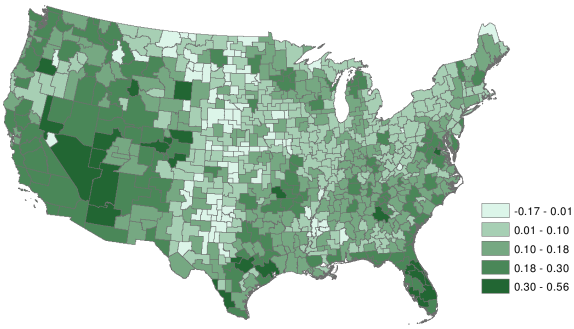
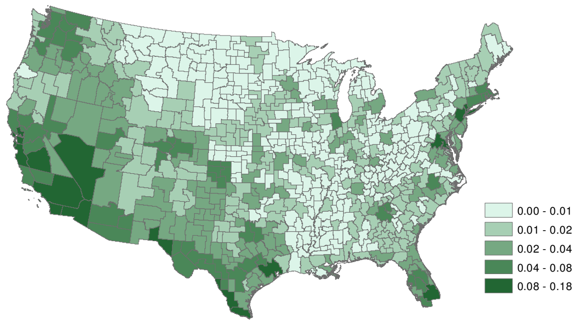


Figure 1: Annual gross flows to US states

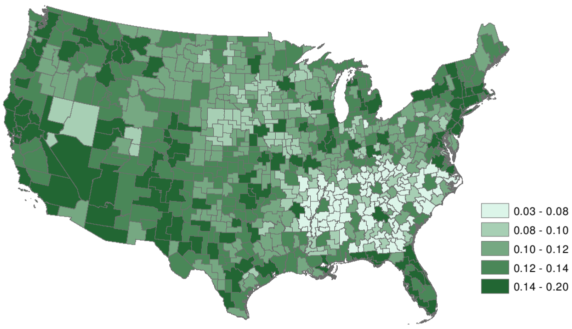
Panel A describes trends in annual gross migratory flows to US states. The "internal" flow is the share of individuals living in a different state (within the US) 12 months previously. The "foreign" flow is the share of individuals who are (i) foreign-born and (ii) living abroad 12 months previously. Panel B reports the share of gross flows to US states (i.e. all individuals living outside their current state 12 months previously) which are due to foreign-born individuals coming from abroad: i.e. the ratio of "foreign" to total flows. Data is based on the the Current Population Survey and US census. See Appendix C.4 for further details.



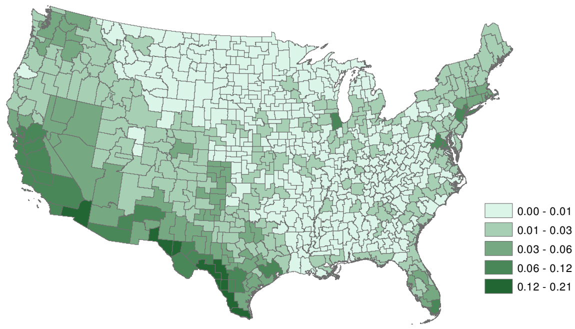
(a) Adjusted employment growth: $\Delta \tilde{n}_{rt}$



(b) Foreign inflow: $\hat{\lambda}^F_{rt}$



(c) Bartik shift-share: b_{rt}



(d) Enclave shift-share: $\hat{\mu}^F_{rt}$

Figure 2: Mean variables of interest by CZ: 1960-2010

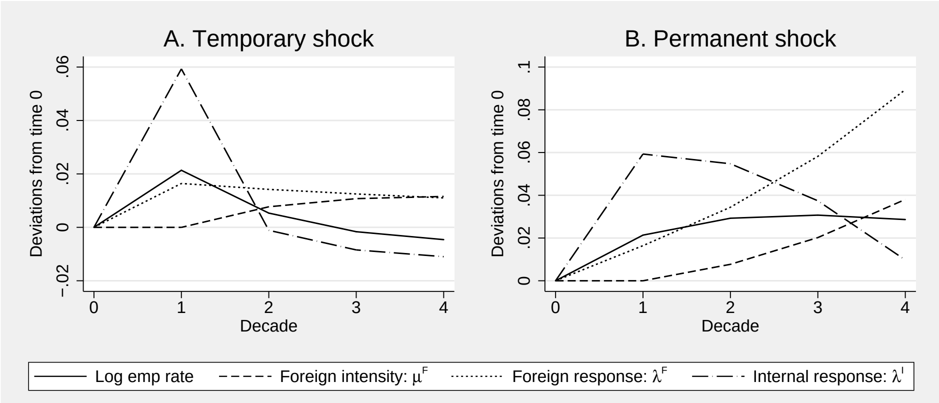


Figure 3: Impulse responses to employment growth shocks

This figure illustrates the impulse response to exogenous employment shocks, $\Delta\tilde{n}_{rt}$. Panel A traces the response to a temporary 0.1 shock at time (decade) 1: i.e. $\Delta\tilde{n}_{rt} = 0.1$ at $t = 1$, and zero otherwise. And in Panel B, I study a permanent 0.1 shock: $\Delta\tilde{n}_{rt} = 0.1$ for all $t > 0$.

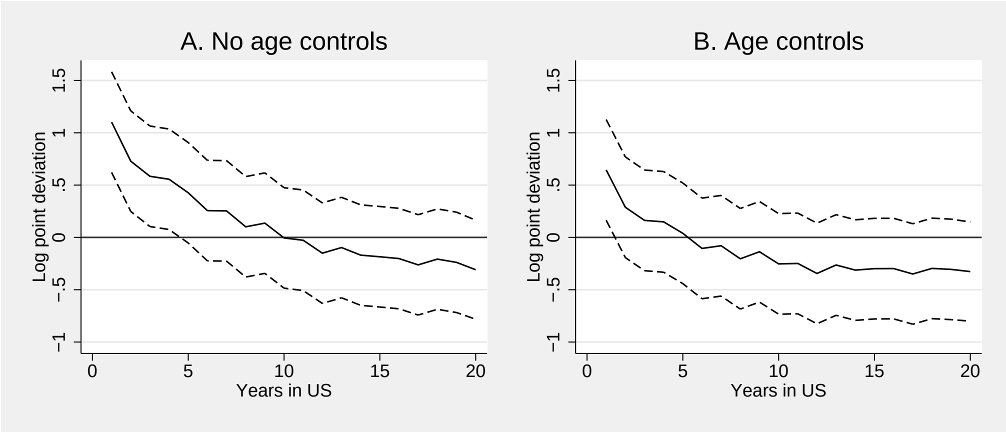


Figure A1: Effect of years in US on cross-state mobility

This figure plots estimates of the log point difference in cross-state mobility between migrants (with given years in the US) and natives. Estimates are based on complementary log-log models, controlling for a full set of entry cohort effects and observation year effects. The model in Panel B controls additionally for a full set of single-year age effects. The sample consists of individuals aged 16-64 in ACS waves between 2000 and 2018. See Appendix D for further details.

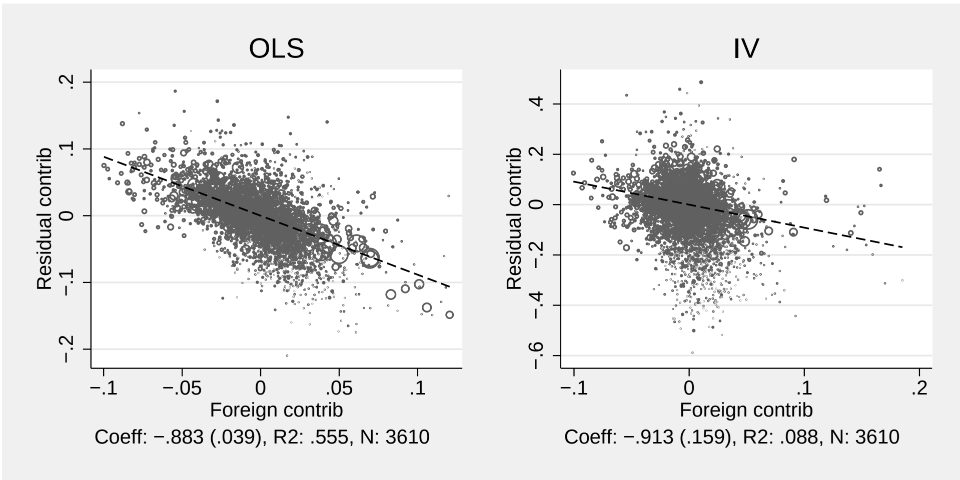


Figure A2: Graphical illustration of crowding out estimates

This figure presents Frisch-Waugh type plots for the δ_1 estimates in columns 1 and 2 of Table 7. Marker size corresponds to lagged population share weights. See Appendix G.1 for details.

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